

Hawalдар, Iqbal Thonse; Ullal, Mithun S.; Sarea, Adel M.; Mathukutti, Rajesha T.; Joseph, Nympha

Article

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Article

The Study on Digital Marketing Influences on Sales for B2B Start-Ups in South Asia

Iqbal Thonse Hawaldar ¹, Mithun S. Ullal ^{2,*}, Adel Sarea ³, Rajesha T. Mathukutti ⁴ and Nympha Joseph ⁵

¹ College of Business Administration, Kingdom University, Riffa P.O. Box 40434, Bahrain; thiqbal34@gmail.com

² Department of Commerce, Manipal Academy of Higher Education (MAHE), Manipal 576104, India

³ Department of Accounting & Economics, College of Business and Finance, Ahlia University, Manama P.O. Box 10878, Bahrain; adelsarea@hotmail.com

⁴ Institutional Assessment Unit, Accreditation & Quality Assurance Centre, Kingdom University, Riffa P.O. Box 40434, Bahrain; rajeshtm550@gmail.com

⁵ Department of Accounting and Finance, Applied Science University, Al Eker P.O.Box 166, Bahrain; nympha.joseph@asu.edu.bh

* Correspondence: mithun.ullal@manipal.edu; Tel.: +91-953-548-3641

Abstract: South Asia has seen a digital revolution in recent years. The number of persons who use the internet has risen drastically. They use it for shopping, social media and online sales. However, there exists a literature gap as far as the effect of outbound digital marketing in B2B markets is concerned. The research builds a model based on brand and consumer interactions in Indian B2B markets using a vector autoregressive model to systemically analyze the cost and outcome of digital marketing efforts by the start-ups operating in South Asia. The multivariate time series analyzed in identifying simultaneous and consistent impacts by the start-ups. We use Vector autoregressive model as it allows us to analyse the relationship among the factors as it changes over time. The research finds evidence for the conceptual framework in South Asian markets. The results prove that sales are greatly influenced by digital media, and outbound marketing efforts, predominantly word of mouth, has a huge impact in building a brand image as it spread over in the social media platforms. It is observed that the digital marketing strategies and consumer interaction are the same across South Asia, but its effect varies from country to country within South Asia thus suggesting a need of developing a new strategy in digital marketing for B2B markets.

Keywords: digital brand-consumer interaction; B2B; outbound marketing; digital media



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1. Introduction

From the last few years, South Asia is observing a steady growth in digital marketing in contrast to offline ads and traditional marketing efforts [1]. The growth is evident in almost all the countries in South Asia where most of them are developing economies, witnessing the substantial increase in social media usage leading to the upsurge in online ads [2–4]. There exists a smaller number of studies on B2B digital marketing, and it is limited to lead generation and customer engagement mostly conducted in western economies [5]. The findings of the western countries cannot be generally applied as South Asian countries are different from the western world [6]. However, the available literature extensively focused on consumer markets and their purchase behaviours [7,8]. The current paper bridges the gap in the literature by studying the digital marketing efforts that can be undertaken by developing economies [9,10].

The study examines all the existing digital media in South Asia and analyses its influence on sales and marketing in the B2B industry. South Asian markets have seen rapid growth of digital marketing firms which connects the sellers to online customers [11,12]. These companies build digital media to create outbound marketing that aims for new sales with online stores. The research applies to brand-consumer interactions which represents

a range of marketing efforts from various firms [13,14]. The research is mainly based on digital communications between the brand and the consumer by studying the outbound digital marketing efforts of start-ups in Asia. The communications are categorized based on numerous characteristics such as level of control and target markets. The outbound marketing efforts are controlled through digital media resulting in inbound reactions, which are managed through webinars on social media, etc. The inbound marketing efforts are represented by the customer reactions online and increased traffic [15]. The study aims to answer the question ‘What are the advantages and inequalities of brand-consumer communications along with its digital environment?’ The study has attempted to answer as to what level the inbound and outbound marketing efforts affect each other mutually. The data has been collected from South Asian countries using exogenous variables vector, where autoregressive model is developed for different types of digital media and where its impact on resulting sales is measured. The data was collected over a year which includes the festival’s sales and New Year break sales. The outcome shows that digital communication between the brands and the consumers in South Asian markets had a positive effect on sales. An increase of 5% in investments in digital media-based ads resulted in an increase in sales by 1.2%. The different types of inbound and outbound ads can be brought together to see to what extent each of them affects the sales [16]. The outcome proves that outbound marketing is a very effective mode of advertising that increases sales in start-ups in South Asian developing economies. Brand consumer communication affects the digital media that captures the customer reaction and generates leads to companies using their digital platforms enticed by the investments in media based on the content, interaction and marketing that is inbound. Forecast error variance decomposition verifies the outcomes [17] giving us the importance of outbound communication. However, inbound communication has a positive effect on sales in B2B. The findings show that outbound and inbound communication deliberate sales, which in turn increases inbound marketing. Research Gap Identified from the study highlights two key points—the extent to which digital communication and sales outcomes influence each other, and the support digital communication offers to brands and customers in B2B markets. So, our main research goal is “Identifying the impact of digital communication on B2B start-up sales in the South Asian market”.

The research question we frame is “What are the forms of digital communication that generate sales for B2B start-ups in South Asian markets”.

Literature review and Objectives:

Digital marketing is the preferred marketing technique by B2B start-ups. The interest in digital platforms and their positive opinions towards social media’s role in business has encouraged the use of digital platforms for B2B markets [18]. B2B markets function on relationships which helps the continuous flow of sales from a single customer. Digital marketing is of high importance as customers now a day, have a wide variety of choices to make and understand the value creation which is of great importance [19]. Existing research on B2B startups has limited role of for customers as sales strategy (make sure this sentence is right.) [20]. An interesting point to be noted is that majority of the B2B start-ups in Asia fail and ideas are abandoned [21]. Now the start-ups in developing countries are harnessing technologies like countries that are advanced [22]. Cold calling had been the most sought-after strategy to acquire B2B customers in South Asia, however now digital technology has taken over [23]. A better understanding of B2B markets can create an impact on the customer in a profitable way [24]. However, a better understanding of this B2B does not exist as it lacks good research in this area [25]. There is very limited literature available on relationships resulting in continuous sales, therefore, giving us no or minuscule information on the topic [26,27].

1.1. South Asian Economy

The characteristics of the South Asian markets differ from the western countries in terms of government policies that influence business sales which in turn affect the

company's ability to get sales in these markets. Other features are the lengthy legal procedures, non-contractual agreements, and business-politics relationships. So, the effects of outbound and inbound marketing on start-ups in South Asia will have a different effect on sales than those experienced in western countries. With the internet penetrating into these South Asian markets start-ups focusing on digital marketing has become the new norm. B2B digital marketing in western countries is wide but in South Asia, it is slowly accelerating but the number of customers availing digital services is comparatively lower. However, in India customers are more involved in social media compared to the western countries. This has been the norm in the past few years, and this is creating more content that helps the marketers. The entry of mobile phones has made these densely populated South Asian countries adopt B2B digital marketing more than others. This helps the start-ups build long term relationships with their customers helping them obtain good reviews for the firms and convert prospects into customers. The start-ups use outbound marketing efforts through their websites and blogs whereas customers initiate inbound marketing by their comments and stories (checked till here).

1.2. B2B Digital Brand-Customer Communication in South Asia

The study concentrates on start-ups, whereas there is enormous research available on big companies in the digital marketing business. The study selected start-ups which only use digital marketing thus helping us to find the right set of data [28,29]. Factors and the mechanisms of the brand and consumer communications will differ in different markets. The government's attitude towards innovation decides the future of digital marketing. The findings will help marketers in developing a good digital marketing strategy for B2B markets in South Asia. The marketers here have always focused on attracting new customers through digital marketing and it is observed that inbound marketing is growing because of ineffective outbound marketing communication with customers. We further move towards explaining the different parts of digital marketing and discuss how important they are in the South Asian markets.

1.3. Aspects of Digital Marketing

The online form of ads in countries like India and China have a high return on investments this leads to conclude that e-commerce portals have high click and sales rates. Digital media is referred to the various digital technologies adopted to sell by marketers [29–31]. These could be websites and social media pages which help customers contact the start-ups. Digital media for our study represents all the digital platforms that can get in touch with its potential customers thus, marketers have given great importance to digital media, consequently informing, and encouraging customers to become buyers. Thus, the study defines digital outbound marketing as the company's investments in outbound marketing over a given period. Social media displays all the activities of the customers besides, the company and firms do not have enough control over these contents as they do in the digital outbound marketing [32,33]. Hence, social media is defined as all customer activity on digital platforms for the given period. The sales developed by clicks in search engines is termed search engine marketing in the current research and the technique is termed search engine optimization [34,35]. The research focuses on search engine optimization as it is preferred more by marketers in South Asia. We use Google to identify the search activities of customers based on the keywords. The research aims to find out how this search engine can be used to predict future sales. Research shows that open innovation like search engine marketing may improve the rankings bringing in more customers. Firms should use such open innovations to advance their technology to markets [36,37]. This open innovation has become a mainstream research idea for companies today [16]. External sources of knowledge along with external sources to market has a lot of potential [38–40]. The companies today look at technology management perspective by integrating the past and current data obtained through open innovation which helps in future decision making [24].

2. Research Approach

Vector autoregressive model is developed based on multiple directional pathways as it allows to consider variables as endogenous [41] and it is tested in western economies and found to be successful in examining the influence of digital and social media on sales [40]. Choices of start-ups in digital marketing and their outcomes are assessed using multivariate time series resulted in identifying simultaneous and consistent impacts [42]. Sixty start-up companies provide us with the data of their digital marketing in B2B in South Asian countries which have started operations in the last three years or less. All the start-ups are in the business of digital marketing being the agent for sellers and buyers. These start-ups manage marketing from online vendors to online customers/buyers. The online vendors could be small e-commerce companies like Bewakoof.com (accessed on 17 Jan 2020) in India or giant retailers like Flipkart from Singapore. These companies do not use any other method of digital marketing, so they suit our need for research.

The digital marketing expenditure data from the selected start-ups were collected on a daily basis where the data spans over 450 days between 2019 and 2020. The variables for example new sales refer to a total of daily sales from the new customers. On a particular day and the B2B acquisitions refer to the number of sellers added daily and the number of customers the firm is adding. Numbers in social media refer to the daily numbers of customer activities on the firm's contents such as likes, shares, comments, etc. Outcomes in social media could be customer reactions that are not company generated [23] which necessarily reflect the attitude of the customers in digital marketing [32]. Audience insights are used to measure the impact of customers' posts on social media and other marketing platforms. The data of companies that opted for payment-based media is collected based on the daily investments on search engines where the start-ups pay for AdWords which led to sales [43]. The next variables are the content created in digital media by blogs and vlogs which the start-ups directly control termed as user-owned media which leads contacts made on the website to a sale [43]. Search engine optimization is the daily inquiries for the start-ups' products on search engines. This variable gives individual clicks on results that are not advertised by online search [19,44]. The variables along with the meanings and references are given in Table 1. The daily average of sales in B2B markets, the customer acquisition per day, social media average per day, and advert variables showing the firms daily spending on outbound marketing are shown in Table A1.

Table 1. Existing literature and variable operationalization.

Sl. No	Variable	Meaning	Theory
1	Social media	The sum of all the customer activities towards the company	Generating customer activities by creating an impression about the brands [45]
2	Digital inbound marketing	The sum of total investments by the firms in inbound marketing	Customised content that engages customers and results in online search
3	Digital outbound marketing	The sum of total investments by the firms in outbound marketing	Ads and sponsored reviews on digital media.
4	New sales in B2B markets	The daily total of sales of the firms with their new customers	The daily new sales in value by digital marketing [21]
5	Payment based media	Daily investment on sponsored ads and AdWords	Increased search ads to increase clicks and converting into sales
6	User owned media	Total of daily contacts from customers on digital media	Number of visits to company website giving customer activity metric

Source: [1,21,23,24,30–32,43,46–50].

2.1. Model

The study follows an empirical approach with systematic marketing where endogenous variables are the inputs and responses. The past time explains the marketing performance and is denoted by t-n. The same methodology is employed to identify the effects

in emerging economies by [1] and we extend this to South Asia markets. This research is based on [1] model known as the VARX model where K is constant and μ is time trend including endogenous variables. An imitation time for operational disruptions for time series is included. Break-even identification for assigning imitation variables was assumed following the repetition method suggested by [40,51] to endogenous variables. To identify multiple disruptions additional tests were employed, as unidentified disruptions are common in VAR models [33]. For time series [33] applied similar framework. The complete structure of the VARX model is shown in Equation (1).

$$\begin{pmatrix} \ln(\text{B2B Sales}) \\ \ln(\text{Payment based media}) \\ \ln(\text{User owned media}) \\ \ln(\text{Outbound media}) \\ \ln(\text{Social media}) \\ \ln(\text{Search engine}) \end{pmatrix} = \begin{pmatrix} K_{\text{B2B Sales}} \\ K_{\text{Payment based media}} \\ K_{\text{User owned media}} \\ K_{\text{Outbound media}} \\ K_{\text{Social media}} \\ K_{\text{Search engine}} \end{pmatrix} + \begin{pmatrix} \mu_{\text{B2B Sales}} \\ \mu_{\text{Payment based media}} \\ \mu_{\text{User owned media}} \\ \mu_{\text{Outbound media}} \\ \mu_{\text{Social media}} \\ \mu_{\text{Search engine}} \end{pmatrix} + \begin{pmatrix} e_{1,1} & e_{1,2} & e_{1,3} & e_{1,4} & e_{1,5} \\ & \dots & & & \\ & & \dots & & \\ & & & \dots & \\ e_{7,1} & e_{7,2} & e_{7,3} & e_{7,4} & e_{7,5} \end{pmatrix} \begin{pmatrix} X_1 \\ X_2 \\ X_3 \\ X_2 \\ X_5 \end{pmatrix} \quad (1)$$

$$+ \sum_{j=4} \begin{pmatrix} \ddot{O}_{1,1} & \dots & \ddot{O}_{1,7} \\ & \dots & \\ & & \dots \\ & & & \dots \\ \ddot{O}_{7,1} & \dots & \ddot{O}_{7,1} \end{pmatrix} \begin{pmatrix} \ln(\text{B2B Sales}_{d-1}) \\ \ln(\text{Payment based media}_{d-1}) \\ \ln(\text{User owned media}_{d-1}) \\ \ln(\text{Outbound media}_{d-1}) \\ \ln(\text{Social media}_{d-1}) \\ \ln(\text{Search engine}_{d-1}) \end{pmatrix} + \begin{pmatrix} \varepsilon_{d2\text{B2B Sales}} \\ \varepsilon_{d2\text{Payment based media}} \\ \varepsilon_{d2\text{User owned media}} \\ \varepsilon_{d2\text{Outbound media}} \\ \varepsilon_{d2\text{Social media}} \\ \varepsilon_{d2\text{Search engine}} \end{pmatrix}$$

Equation (1) has similar representations to that of [1,45], d indicates day and constraints \ddot{o} indicate the direct and indirect effect among the variables in the system. Along with constant terms, time trends were also involved. The key factor in the study is the error vector ε_t after the Cholesky decomposition of the error terms was used in all ordering of endogenous variables [45]; there is no causal ordering [33]. In supplying the average results of decision variables, the prediction of all VARs with numerous numberings develops the forms of media preference in South Asian markets.

2.2. Conditions of the Model

The study measures the interrelationships between variables and sales using the VARX model and the goal that assures the model can develop variables [22,33]. First, Granger causality tests [25] were used to check the endogenous factors among variables in marketing with bidirectional (refer to Table 2). Also, analysing the unit root in model variables by structural disruptions test as referred by [52], we find arrangements that are uneven by assessment. Hypothesis testing is done to see whether a variable has a unit root with structural disruptions in trends & intercepts [20].

Table 2. Existing literature and variable operationalization.

Sr. No.	Methodology	Description	Specific Process
1	The endogeneity between marketing variables is analyzed [2]	Granger causality tests for each pair of variables	Daily data collected is tested for endogeneity between model variables [25]. The p values lowest numbers are reported across delays.
2	Estimating the VARX model followed by cumulative instinct response	The ordering of endogenous variables in the VAR is changed using Cholesky decomposition of the error term	We calculate the relative effectiveness of digital media [45] along with their collective elasticities and effects based on averages. The contemporaneous correlation problem among error vector elements is solved using the Cholesky decomposition method.
3	Alternative models comparison	The estimated model is compared with the alternative model.	Multiplicative models are used for comparison using dependent variables and means and autoregression of endogenous variables.
4	Unit root test [52]	Predicts a break in intercept and trend that's structural or multiple	Endogenous breaks exist in the system, unit root tests on different transformation variables were conducted [53] to test structural breaks. Only stationary variables were found thus no cointegration is needed.
5	In sample forecasting with estimated VAR [41]	75% of the data was used to estimate and the rest to validate	The tests were done for new sales.

The structural disruptions may misrepresent the test with variables displaying a range of mechanical pauses of numbers that are unknown along with their forms & durations [54]. On testing the structural disruptions showing the existence of changes to means. It gives additive outlier and the improved outliers procedures in model variables in levels as given by. Statistics along with the conclusions of the test of a unit root in root variables are given in Table 3.

We look for breaks in variables showing change in their means. We start by checking for basic break test conducted prior to unit root test which was conducted to overcome irregular patterns [55].

Table 3. Structural breaks along with Unit root on model variables.

Variable	Improver Outlier			Innovation Outlier			Analysis
Payment based media	24.12 ***	−5.21 ***	−2.65	18.11 ***	−11.12 ***	−18.72 ***	Structural break
New sales	3.48 ***	1.12	−7.68 ***	4.17 ***	0.18	−10.28 ***	Multiple breaks
Search engine	2.91 ***	1.02 *	−6.16 ***	2.24 ***	2.07 **	−8.14 ***	Multiple breaks
User Owned media	−2.45 ***	5.49 ***	−3.89	−5.76 ***	6.45 ***	−6.75 ***	Multiple breaks
Social media	−5.78 ***	−6.12 ***	−2.02	1.46	−1.62 **	−2.74	Multiple breaks
Outbound media	8.23 ***	6.86 ***	−1.12	22.21 ***	10.12 ***	−22.21 ***	Multiple breaks

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Improvement outlier's records mean structural breaks in t-statistics are shown. Innovation outlier shows a shift in the mean. Structural breaks T-statistics for significance are exhibited. Reference [56] the hypothesis of unit roots is shown in all series. The critical value is −4.48 (5%) for all of them.

2.3. Outcomes

Collective compulsion responses are generated after identifying the VARX models as shown in Table 2. After prediction for the errors, the Cholesky decomposition is tested. The ordering of endogenous variables is changed in the VAR system. It helps in calculating and comparing the relation value [45] between various digital marketing along with their effect and elasticities. The problem of concurrent correlation is solved by Cholesky decomposition among features in the error vector [57] and work the same as experiments conceptually.

We then compare the estimation model with other models to examine performance by conducting sample forecasts as shown in Table 2. VARX model compared with time series model founded on autoregressions and mean of endogenous variables. On comparing elasticities developed by instinctive reaction roles of VARX beside multiplicative models by reaction variable as the dependent variables (this is not making sense). The potential indigeneity in empirical development can be a result of plans set by the firms in using digital media. VARX model shows elasticities are reliable compared to alternative ones.

3. Findings

3.1. Collective Elasticity

The relationship between brand and consumer communication components is examined. The average of these increasing elasticities of multiple media's layouts on the chief response variables calculated subsequent a replication in all the possible ordering is shown in Table A1 [43]. Deploys diverse orderings to identify the understanding of elasticities. The results indicate that expenditure on digital media is more compared to sales in B2B. The B2B sales elasticity for outbound marketing are given in Table A1. Digital media and outbound marketing affects the two-response variable more compared to other variables.

Social media elasticity for new sales and search engine elasticity for B2B markets are shown in Table A1. We found user-owned media and outbound marketing give a medium positive effect on the response variable with some effects reverting to positive influence. The cyclic influence of performances and digital media is evident from Granger

causality tests. Similarly, outbound and inbound marketing have bi-directional effects on performance metrics which in turn affect digital media in cyclical performance. This shows that multiple media interact and the recurring response influences B2B sales.

3.2. Collective Instinct Response Functions

Development of these elasticities is evaluated by seeing the response of performances by the collective instinct response function of the VARX model. The instinctive responses on social media and search engines achieve their highest sales ahead which are shown in Table A1 while instinctive responses in user-owned media and outbound marketing are stable showing high elasticity. Positive form in these elasticities shows an extra effect that spreads beyond the ad timings. There exists a positive effect on user-owned media in B2B sales, a 5% increase in response on user-owned media attains 56% new sales. This pattern is also observed in outbound marketing with lower elasticities from 0.04 to 0.09.

3.3. Response Variables

The collective orthogonalized instinctive reaction of outbound marketing and owned media is shown in Figures 1 and 2. The effect of imitations from different VARX orderings is shown in the black line with a 90% confidence level. This gives us a positive and cumulative impact of outbound marketing on sales. The effect of user-owned media is also found to be positive. The new sales are shown in Figure 3. As per [41] we use 75% data as an approximation sample and the rest as confirmation. An extra process for comparing the projected VARX model besides the rival model is conducted through autoregression of endogenous variables. This model is suitable for analysing the pattern investments in media and performance of marketing companies in South Asia.

3.4. Alternative Multiplicative Models

To identify the dependability of the VARX model, an alternative multiplicative model is developed to question this estimate. This consists of all strategies used in digital communication as independent variables and resulting sales as a dependent variable. Here we test the elasticities and match them with VARX by instrumental free method [58] using Gaussian Copula Transformation.

$$\text{Copulaxt} = O [HxKxt]$$

Hx is the empirical cumulative distribution function of the variable and \hat{O} gives the inverse distribution meaning of the standard normal [8]. The Copula converts daily contact by potential clients as user-owned media thus concerns of endogeneity are not likely. Hence new sales in B2B markets are the model's response variables and Gaussian Copulas are the control functions of the response variables. The model is built on [58] equations where Copula is added along with endogenous variables.

An alternative model for new sales:

$$\ln \mu \text{ New B2B Sales } \beta_d \frac{1}{4} \ln \frac{1}{4} \beta \beta_{11} \ln \mu \text{ Social media } \beta_d \beta \beta_{21} \ln \mu \text{ Payment based media } \beta_d \beta \beta_{31} \ln \mu \text{ Digital media } \beta \beta_{41} \ln \mu \text{ Outbound marketing } \beta_d \beta \beta_{51} \ln \mu \text{ Search engine } \beta_d \beta \beta_{61} \ln \mu \text{ Copula-Social media } \beta_d \beta \beta_{71} \ln \mu \text{ Copula-Payment based media } \beta_d \beta \beta_{81} \ln \mu \text{ Copula-Outbound marketing } \beta \beta_{91} \ln \mu \text{ Copula-Search engine } \beta_d \beta \ln \epsilon_d$$

Copula transformation is used after identifying familiarity defilement prediction with the Shapiro Wilk test of normality. Outcomes of digital media variables were observed at $p, 0.001$ and the study computed standard errors for factors predicting. RESET (Ramsey Regression Equation Specification Error Test) is carried out for left out variables and the Breush Godfrey LM test is conducted for autocorrelation on both regression models after estimation. The outcomes of VARX models showing elasticities concerning other multiplicative models are shown in Table 4.

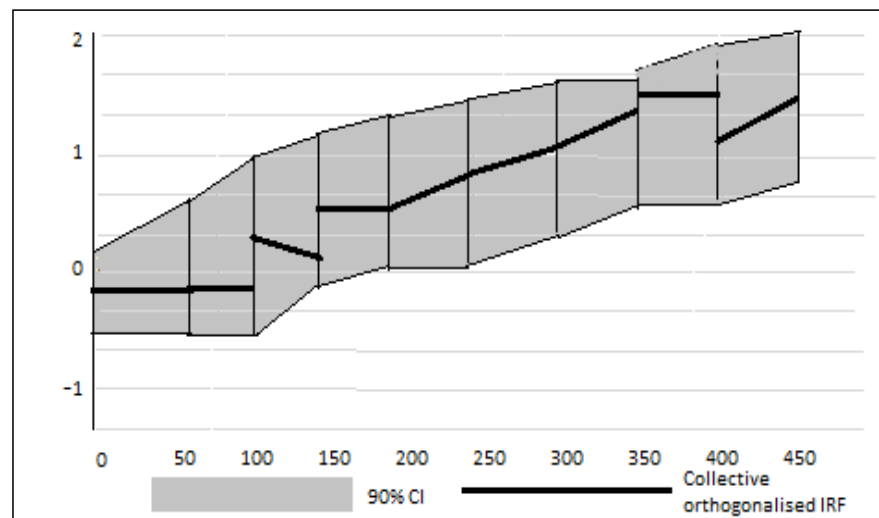


Figure 1. Digital Outbound Marketing.

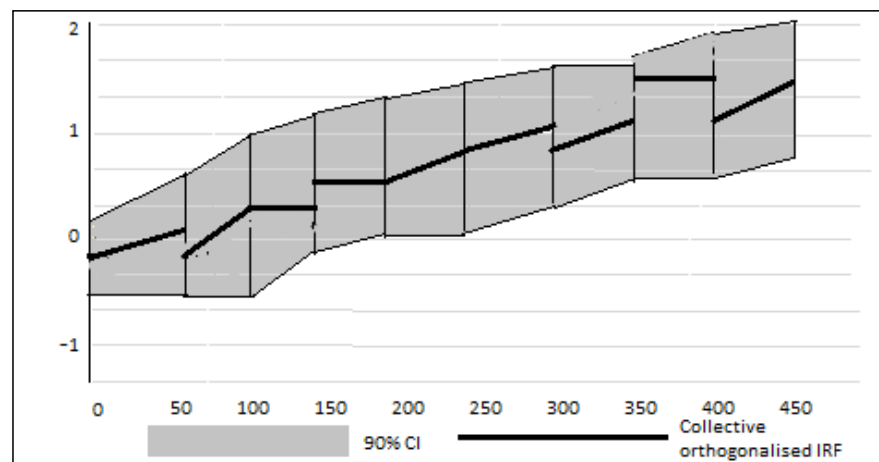


Figure 2. Owned Media Marketing. Source: Collective orthogonalized instinctive response of outbound and user-owned media on new sales.

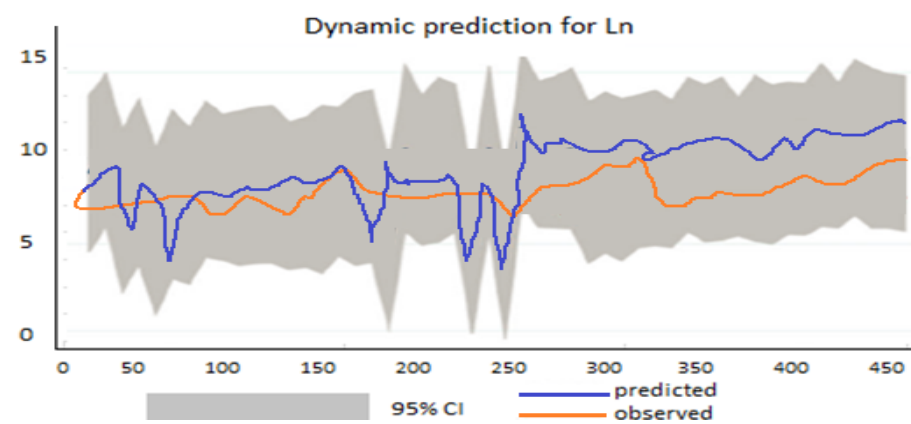


Figure 3. Dynamic prediction of the response variable.

Table 4. Average collective elasticities of different digital medias.

New Sales in B2B Contemporaneous	Instinct on Payment-Based Media		Instinct on User-Owned Media		Instinct on Search Engine		Instinct on Outbound Marketing		Instinct on Social Media	
	M	SD	M	SD	M	SD	M	SD	M	SD
Contemporaneous	−0.07	0.10	−0.11	0.11	−0.05	0.07	−0.12	0.14	−0.08	0.10
1	0.07	0.11	0.13	0.07	−0.12	0.09	−0.08	0.14	0.05	0.12
2	0.12	0.13	0.31	0.06	−0.06	0.11	−0.01	0.13	0.11	0.14
3	0.05	0.12	0.22	0.05	−0.01	0.10	0.06	0.12	0.06	0.12
4	0.04	0.11	0.43	0.04	0.16	0.11	0.31	0.11	0.04	0.11
5	0.03	0.12	0.56	0.05	0.14	0.11	0.51	0.10	0.03	0.11
6	0.10	0.11	0.71	0.06	0.18	0.12	0.71	0.09	0.10	0.12
7	0.06	0.14	0.81	0.06	0.12	0.11	0.07	0.10	0.06	0.12
8	0.08	0.13	0.78	0.05	0.11	0.14	10.1	0.09	0.08	0.16

M—Mean, SD—Standard Deviation.

4. Discussion

Digital marketing as a part of open innovation has many ways to be implemented in marketing [25,59–61]. Companies need to open up these innovation process to create business value [24]. Major companies today get most of their revenue from services rather than products [37,62]. Digital marketing service has changed the way marketing is done today which began in western countries and continued into South Asian markets. Today customer purchases and consume with an increase of information in the digital world driven by open innovation (incomplete sentence). Our outcome adds many things to the existing literature on digital marketing such as, explaining the strong relationship between user-owned media and sales in comparison to all other types of marketing. The content advertisers posted on their websites will assist companies to influence customers through their media activity. The content in digital media should be developed based on a choice of specific keywords (see Table 5).

Table 5. Gaussian Copula model coefficients.

Variable	An Alternative Model for Ln for New Sales			
	Coef	Bootstrap SE	Z	p (z)
Ln (Payment based media)	−0.21	0.28	−0.78	0.32
Ln (Outbound marketing)	0.16	0.21	0.71	0.39
Ln (User owned media)	0.35	0.16	1.86	0.03 **
Ln (Search engine marketing)	0.21	0.16	1.12	0.16
Ln (social media)	0.22	0.29	0.68	0.39
Controls				
Copula term-Ln (Payment based media)	0.41	0.56	0.67	0.42
Copula term-Ln (Outbound marketing)	0.04	0.41	0.09	0.78
Copula term-Ln (Search engine marketing)	−0.18	0.36	−0.51	0.52
Copula term-Ln (social media)	−0.51	0.34	−1.19	0.16
Constant	3.38	0.98	3.21	0.00 ***
R ²	0.23			

Table 5. Cont.

Controls	
Adjusted R ²	0.22
Ramsey RESET test	1.18
LM test chi-square	0.78

*** $p < 0.01$, ** $p < 0.05$.

The outcomes in Table 5 of our research also show a weak relation between social media and sales. Certain aspects of digital media play a very important role in digital marketing which we would like to bring to the notice of digital marketers. The perception is that payment-based media will increase sales as customers will be well informed. However, our empirical findings suggest that payment-based media generates fewer sales (Table 6).

Table 6. Granger causality test, correlation, and structural break test.

Granger Caused by		Focal Variable				
	New Sales	Payment Based Media	Outbound Marketing	User Owned Media	Search Engine Marketing	Social Media
New sales	-	0.04	0.00	0.02	0.01	IS
Payment based media	IS	-	IS	IS	IS	IS
Outbound marketing	IS	IS	-	IS	0.04	IS
User owned media	0.01	IS	0.02	-	0.02	0.02
Search engine marketing	0.04	IS	0.00	0.06	0.04	IS
Social media	IS	0.02	IS	0.05	IS	-
Correlations						
Ln New sales	1					
Ln Payment based media	0.17 **	1				0.38 ***
Ln Outbound marketing	0.18 **	0.56 **	1	−0.16 **		0.21 **
Ln User owned media	0.08	−0.21		1		0.06
Search engine marketing	0.04	0.03	0.09	−0.01	1	0.07
Ln social media	0.11					1
Descriptive Statistics						
Mean	1878.21	139.22	864.34	40.32	11.25	43.21
Std. deviation	1902.65	155.45	912.21	22.12	10.24	138.58
Min	0.00	0.00	0.00	0.00	0.00	0.00
Max	840,000.00	696.12	2515.21	87.00	45.12	1122
Structural Break Test						
Ziyot and Andrews(1992)	−11.02 ***	−4.45	−6.65 ***	−7.04 ***	−9.12 ***	−11.114 ***

Bidirectional causality among variables insignificant. No. on cells for Granger causality tests are minimum p -values across delays. Correlation between model variables is de-trended *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, IS—Insignificant.

Digital marketers in India and China are using inbound marketing to create content to influence customers buying decisions. The crucial finding of our study is that inbound marketing shows a very important part in bringing the sale numbers as the content gets leads and leads contribute to sales. The sales are higher when the startups invest in customer content-based digital marketing platforms. All this comes together to form the digital brand-customer communication which is repetitive, and which shows the connection between brand, customer and digital media. We prove how various digital components

affect sales in B2B markets in South Asia. This could be applied to developing markets across the world by the marketers of the companies.

5. Conclusions, Future Implications and Discussion

We conclude that the effect of payment-based media is negative, but it can be of interest to identify to what extent it is negative by future researchers. Also, furthermore, in the future, researchers may not limit their study to digital marketing and take traditional form of ads into the cycle of communication created by marketers between brands and the customers in future. The findings of the study contribute to the existing body of knowledge concerning the role of digital marketing in the case of B2B sales by introducing and examining the content-based media which generates leads and increases sales. This study is unique in its way, as it has investigated the effect of digital marketing on sales in B2B markets of south Asia only. Vendors can use these outcomes to sell in South Asia and future research can cover entire Asia as the market. The study is based on digital communication between brand and customer whereas in future, the researchers can focus on all the communications working with companies who use all forms of ads and not just digital ads.

The previous studies were limited value creation targeting sales in developed countries. Vieira (2019) had found earned media along with inbound marketing to be more useful than paid media [26]. We have focused on how South Asia which is predominantly developing is implementing digital marketing to generate leads and final sales. The study throws light on which aspects of digital marketing can increase sales and it proves how social media does not influence sales. Our finding is similar to Vieira (2019) on payment-based media [26]. We further have identified various digital components and their effect on sales. Hofacker et al. has identified the trends in digital marketing but has not delved into social media and paid media. Van Esch & Stewart Black have found the effect of AI but this study goes into the intricacies of digital marketing and finds the various aspects that actually generate sales and not limited to one aspect.

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Appendix A

Table A1. Average collective elasticities of digital media on multiple response variables and FEVD.

Digital Marketing	Effect of 5% Instinctive	Response to New Sales			
		Mean	SD	Min	Max
Outbound digital-communication	Payment based media	0.12	0.11	0.24	0.14
	Outbound marketing	0.29	0.38	0.31	1.16
	User owned media	0.36	0.19	0.16	1.02
Inbound digital-communication	Search engine marketing	0.03	0.14	0.24	0.32
	Social media	0.04	0.11	0.27	0.35

Table A1. *Cont.*

Error	Variables	FEVD of New Sales			
Error variance decomposition of media	User owned media	0.03	0.01	0.01	0.07
	Outbound marketing	0.02	0.02	0.00	0.10
	Search engine marketing	0.01	0.01	0.00	0.03
	Social media	0.02	0.01	0.01	0.04
	Payment based media	0.00	0.00	0.00	0.01

Collective elasticities with the total of all VARX orderings. Average effects representing is shown in the form of means.

Table A2. Test for VARX and Lagrange multiplier test for autocorrelation of fitted VARX model.

D	LL	LR	FPE	AIC	HQIC	SBIC	D	chi ²	df	Prob > chi ²
0	−122,32.74	–	4.602	20.468	20.082	21.768	1	48.12	49	0.27
1	−902.012	712.12	0.0198	14.128	16.168 *	17.129 *	2	58.12	49	0.07
2	−802.512	102.04	0.01564 *	15.127 *	16.468	17.237	3	42.12	49	0.41
3	−802.768	68.217	0.0286	15.224	17.162	18.128	4	49.42	49	0.29
4	−702.721	98.65*	0.028	15.122	17.568	21.002	5	48.12	49	0.38

* Indicates the delay order selected for each criterion and Lagrange multiplier no autocorrelation at lag order, D-Delay.

Appendix B

Table A3. Unit roots and structural break routines on model variables.

Variables	Improver Outlier Routine			Innovation Outlier Routine			Final
	1st Break	2nd Break	(rh − 1) ³	1st Break	2nd Break	(rh − 1)	
New B2B Sales	3.24 ***	1.02	−8.12 ***	3.12 ***	0.29	−8.24 ***	STSB
Ln(New B2B Sales)	2.89 ***	0.98	−7.28 ***	3.28 ***	0.18	−10.11 ***	STSB
User owned media	−2.01 **	6.00 ***	−6.27 ***	−1.98 ***	3.68 ***	−6.68 ***	STSB
Ln(User owned media)	−1.98 ***	5.12 ***	−3.18	−5.14 ***	6.12 ***	−6.12 ***	STSB
Social media	1.68 **	−1.21	−2.98	1.12	−1.12	−5.12 ***	STSB
Ln(social media)	−5.12 ***	−5.86 ***	−2.12	1.68	−1.28 **	−2.12	STSB
Digital outbound marketing	16.12 ***	17.12 ***	−1.42	7.12 ***	7.12 ***	−9.12 ***	STSB
Ln(Digital outbound marketing)	28.14 ***	6.12 ***	−1.12	21.19 ***	11.12 ***	−21.27 ***	STSB
Payment based media	18.22 ***	−11.48 ***	−2.41	4.32 ***	−2.21 ***	−4.24 ***	STSB
Ln(Payment based media)	34.12 ***	−5.86 ***	−3.12	19.21 ***	−11.23 ***	−19.28 ***	STSB
Search engine marketing	3.48 ***	3.28 ***	−3.27	2.12 **	2.12 ***	−3.32	STSB
Ln(Search engine marketing)	3.12 ***	1.42 *	−6.12 ***	3.12 ***	2.12 **	−9.11 ***	STSB

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; STSB refers to stationary with a structural break; The sudden means is recorded by improver outliers. T-statistics for structural breaks significances are displayed. Innovation outlier allows for a shift in the mean of a series. T-statistics for structural breaks significances are displayed.

Appendix C

Table A4. RMSE of simulated out of sample forecasts, VAR tested with an alternative method.

Variable	Horizon (Periods Ahead)	Method				% of Improvement		
		Mean	Random Walk	AR	VAR	Mean	Random Walk	AR
Ln(New B2B sales)	2	1.12	0.6	1.34	0.49	54	14	58
	4	1.13	0.74	1.37	0.59	52	21	56
	8	1.24	1.12	1.45	1.02	29	8	32
Ln(social media)	2	2.12	1.23	1.78	1.35	21	−14	21
	4	2.11	1.21	2.01	2.01	1.89	−41	0
	8	2.02	2.01	2.01	2.37	−12	−22	−12
Ln(Payment based Media)	2	2.54	0.49	2.3	0.51	65	−29	67
	4	2.42	0.48	2.35	0.78	62	−38	61
	8	2.38	0.59	2.46	1.02	51	−71	44
Ln(User owned media)	2	0.8	0.31	0.88	0.41	42	−27	41
	4	0.82	0.32	0.89	0.51	27	−42	38
	8	0.8	0.39	0.88	0.67	18	−62	21
Ln(Digital Outbound marketing)	2	3.36	0.12	3.47	0.21	78	−41	78
	4	3.59	0.19	3.4	0.28	89	−28	78
	8	3.46	0.29	3.36	0.37	78	−17	76
Ln(Search engine marketing)	2	1.12	1.02	1.22	0.86	24	11	21
	4	1.26	0.79	1.27	0.64	38	9	36
	8	1.19	0.84	1.29	0.66	42	16	38

RMSE for all prediction and percentage improvement of VAR forecasts with alternative methods.

Appendix D

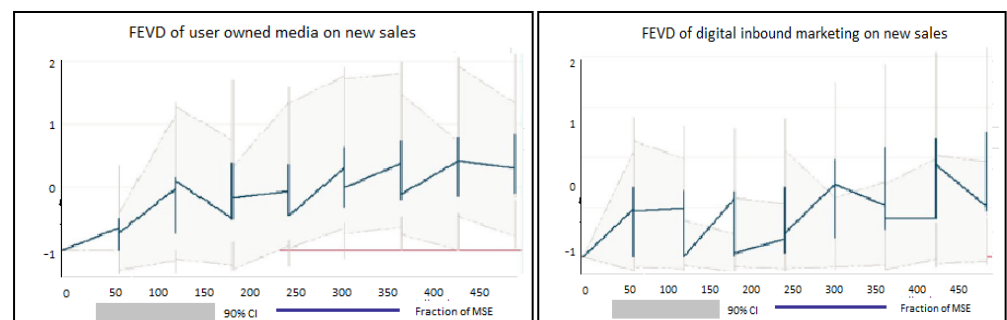


Figure A1. FEVD of new sales by digital inbound marketing.

Appendix E Assumptions of Alternative Models

The model is nonlinear in constraints to linearize; logarithmic transformation was used in multiple log format. The elasticities of new sales can be retrieved from the estimated betas [62]. The limitation could be the potential endogeneity of coefficient could be biased. So, we use Copula transformation [37]. The autocorrelation and general specification testing were done by specifications. We thus derived steady multiplicative models for developing interpretable elasticities.

The nature of these models is another limitation along with its implications of predicted elasticities. Thus, we use VAR [51]. This records the dynamic effects in everyday sales as it is projected in our digital brand and consumer model.

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