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BIG DATA AS A TOOL FOR TUNNEL MARKETING

Abstract

Purpose – is to describe the relationship between Big Data and personalized marketing. This work's object is to clarify how Big Data can become a point of new visions on marketing activities designed to customers and potential consumers.

Methodology – Quantitative research is applied for this study to collect the amount of companies that has already used Big Data tools and their ability to create content that is most applicable by customers. Non-random sampling method is used in this study due to limit in time resources and money resources. In order to gather data about customers behavior toward advertisements through digital and non- digital tools and their purchase intention arising from these advertisements, random sampling method was applied.

Originality/Value – Given research can be helpful to explain how Big Data can strengthen the effectiveness marketing activities of companies. Usage of Big Data can lead to get deeper knowledge about consumers of companies that will make these companies closer to their consumers. This research is also showing how marketing costs are reduced by using Big Data as a marketing tool that will help to avoid wastes. Big Data must be learned as a potential for marketers to increase the effectiveness of their activities with efficient inputs. It is important to understand how this software is able to solve any particular problems that marketing people face in the real business conditions.

Findings – Implementing Big Data as a marketing tool can helpfully strengthen marketing activities by collecting and absorbing information about clients and create personalized content. This content will have an effect on capacity of customers that company has and it depends on how the information collected and analyzed by Big Data will be directed and used. From provided (ANOVA) test of H3 we can see that the difference in the number of customers present according to presence of Big Data as a tool in operations. Which showed that companies will have more clients when Big Data is applied. In the case of test of H4 (table 10), the direction from attention to purchase intention is constructed. The significant difference exists in all concepts which have been applied as components on the way to purchase intention of customers.

Key words – Big Data, personalized marketing, customer capacity, purchase intention

1. Big Data

The term Big Data appeared relatively recently and despite this managed to win a lot of interest. Not everyone knows and understands what it means and why it was created. Big Data is dynamical and variant volumes of data generated by people, machines and all kinds of modern tools; it requires innovative and massive technologies that are used to collect, analyze and post a huge amount of data collected for real-time information about the business, which is connected with profit, consumers, productivity management, risks and increase in shareholder value. Big Data includes data retrieval from social networks, mechanic data, data taken from Internet-enabled devices, voice records and video, as well as the registration and storage of both structured and unstructured data. Big Data can be characterized by four «V" (Ernst and Young, 2014):

– Volume: compared to conventional data sources the amount of data being created is enormous;
– Variety: data is being created by machines as well as people comes from different sources;
– Velocity: data is being generated exceedingly fast — a process that never stops;
– Veracity: big data is obtaining from many different sources, as a result you need to test the quality of the data.

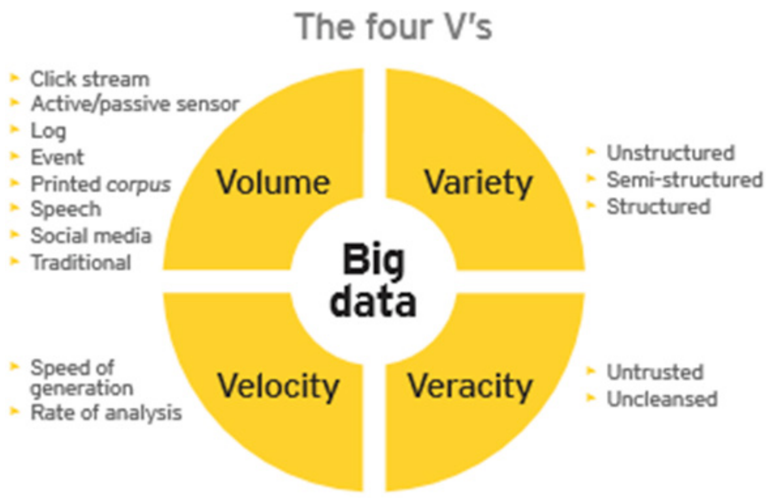

Figure 1 – The four Vs of Big Data

The outlook for the future is becoming more important than the usual visualization of current or historical perspectives, especially in an ever-changing business environment. For more effective future forecasting, data analysis uses statistical and predictive modeling techniques that can be used to maintain and improve the organizational business strategy (Dapp & Heinie, 2014). Organizations can develop their own analytical capabilities, as well as opportunities that are available only to a few larger organizations over the years, thanks to the collection and the announcement of a big date and other information that is outside the business.

While marketing is about achieving the correct customers at the perfect time, Big Data can be utilized to anticipate purchases, break down client conduct and better comprehend the general population purchasing your item. Yet, numerous organizations are deadened by the sheer measure of data and think that it's difficult to distinguish noteworthy wellsprings of client understanding.

2. Big Data Analytics

Marketing managers are scanning for and fail to discover customer experience strategy to successfully apply information and examination. They're looking to information to help enhance client travels and convey more important (and productive) encounters through personalization (Wheeler, 2016). Big Data analytics (BDA) is used for the compilation of statistics and for carrying out drifts that are associated with the most prospective clients (clients whose life assessment deserves attention, rather than combining the costs of maintenance and deduction) and compare them with the audience profile. And also, to identify and monitor the most important clients that correspond to a certain profile (Klum, 2016). BDA can help organizations extract useful information from complex, huge, diverse and interrelated data sets that lead to valuable representations (such as customer behavior and the condition of the business). In 2009 existed a very small amount of the big data enterprises, the least total revenue in this industry was less than $100 million (Seguine, unknown year). Based on Deloitte estimates, more than 90% of the Fortune500 list had some large enterprises to provide a Big Data in 2012, which led to an industry revenue increase of up to $1 billion (Lee & Steward, 2012). Venture capitalists subventionize Big Data projects with funding in a surplus of $50 million (Berman, 2012), and governments subventionize large data and open data projects (Harris, 2012). Apparently, the data is a source of value.

Data analytics has other forms: analysis of web-traffic and analysis of customer satisfaction are some of them. Even though for each form of data analytics there is a different way to create value, the objective is almost the same for everyone: increasing profitability or reducing costs, and sometimes both. The term big data is still incomprehensible, probably because the big data is not a tangible concept or a fixed property. The big data is a steady innovation, rather than a destructive innovation, which makes it difficult to define, describe and distinguish the BDA from traditional data analytics. For example, when analyzing web traffic comes understanding, which further improves the use of the website, which directly leads to more satisfied customers and increased sales. Continuing the big data analytics themes, the question comes to mind: the big data of analytics is different from the traditional data analytics. Nevertheless, BDA can also support traditional data analytics, also mentioned by Adrian & Chamberlin (2012).

3. **Tunnel Vision in Marketing**

Denis Corcoran (2011) connected notion of tunnel vision with marketing phenomena and which symptoms it able to bring. He claimed that over 85% of all organizations experience the ill effects of a benefit debilitating sickness called Tunnel Vision Marketing. According to his study, tunnel vision in marketing is a visual deficiency about who your customer is, what influences them to tick, what they are profoundly feeling, and so forth. In the event that your business is in survival mode, leveled or enduring minimal execution, it is most likely experiencing Tunnel Vision Marketing. Marketing team spends so much time with daily activities: social media, email campaigns, updates to the website, the white paper someone decided they needed, supporting Sales, that there's no time to get the bigger picture of the audience (Ioanăs & Stoica, 2014). The greater picture is basic to guaranteeing the substance you create is addressing the requirements of your target market (Baumgartner & Steenkamp, 1996). You have to cut out time to venture back and distinguish your personas.

McKinsey quarterly (2009) suggested the "funnel" metaphor according to mutual action between marketing of company and consumers. But nowadays this funnel structure is about to fail because of market explosion and intangible communication decrease. This failed funnel led to complicated decision-making process of customer which can influence marketing activities of company. The model of funnel of McKinsey is based on agenda of consumer-driven marketing and called as consumer decision journey. This journey is a path from awareness to purchase and loyalty, but the problem of creating awareness comes from mass product appearance while companies work up marketing activities for market shares. Their findings also showed the shift from one-way communication to mutual communication, that is where Big Data tools can play a significant role and awareness must appear. Digital tools can be applied to use gathered information to communicate with customers.

1.1. Big Data, the perfect instrument for predicting and study consumer behavior

From the point of view of studying the behavior of consumers, Big Data helps to extract more information in this area, thereby enabling customers to improve their buying experience, for example, customer loyalty, customer segmentation, acquisition and promotion analysis, priority analysis, seasonal sales analysis, customer-specific approach, consumer segmentation, basket analysis, cross-selling analysis, the communication channel, the analysis of the winning and losses, and so on (Berman, Previte & Fry, 2016).

American Marketing Association defines marketing research as process in which the connection between opportunities and problems are taken under review through the information collected by managers from customers (Stoicesu, 2015). Big Data directed to educate consumer behavior has an ability to gather variety of data leading to process information that would be assessed as source to get knowledge of customer experience (Fang & Li, 2014). Today customers became more informed in case of purchase goods and services and aspect of purchase decision has changed (Gamble, Tapp, Marsella & Stone, 2005). Through machine learning analysis, possibility of education customers factors, acquisition, priority and sales related data become more detailed indeed, shifts and associations are also considered from this learning (Kurt, 2015). Big Data create a strong bond between hesitating consumer behavior with business decisions by ability to analyze consumer factors that affect customers decision making (Stoicesu, 2015). Consumers make decisions in real-time concept, to understand customers better it is necessary to collect as more data as possible in real time. Analysis of the collected data can lead to how to correctly guide customers by better addressing their needs and strengthen the bottom line. Occupancy of algorithms collected and processed by Big Data has an allowance to match consumers' needs with right products by determination of characteristics that cross with customers' needs and wants (Fang & Li, 2014). Machine learning also gives an opportunity to anticipate what customers will want, before he/she makes a final decision. Utilization of collected info construct the image of potential consumers' willingness to purchase more specific specter of goods or services that is able to satisfy their needs before they understand that this need has occurred (Kurt, 2015). In this way customers get what they want before they are looking for it (Ryan Kh, 2016).

Certain studies were conducted explaining how Big Data is used in marketing performances by collecting and analyzing info about customers, like brands that they are loyal to, seasonal trading and etc. According to C. Stoicesu's work (2009) Big Data is the best tool in order to study consumer behavior. In her work she mentioned the amount of information that Big Data is able to process with high level speed. This aspect is not the limit, this huge amount of data consists of not only wide specter of information, but also the deepness was considered. Cristina claimed that Big Data is able to work on hidden parts of behavioral pattern of customers and prospects. She also concerned that classical way of collecting data about consumer behavior is more statical and less qualitative. This claim lead to lack of accuracy in construction of effective customized marketing campaigns directed to customers and companies fail to reach each customer on a personal level.

Personalized marketing activities are based totally on customers' profile that constructed from analysis of their particular behavior (Linzmajer, et al. 2015). Demographic data and preferences are concerned through the analysis determining the differentiation of customers' profiles (Keller, 2001). Consumer behavior is the discipline studying customers' needs and tastes and what response they give to products' marketing. As more understandable picture of customers' needs and tastes as more personalized marketing activity is willing to be directed to targeted segments (Liang, Lai & Ku, 2007).

From this perspective, we can assume that Big Data is a direct killer of risk that arises from tunnel vision in marketing aspect; it has an ability to construct a mental «portrait» of a customer or a prospect. Big Data functions connect pieces of qualitative data about consumers' personality anticipating his pattern to purchase, so companies will be able to adopt tunnel marketing program directed to every customer on individual level.

1.2. Big Data and Personalized Marketing

Studies have contended that buyers ordinarily get a kick out of the opportunity to make purchase through the same stores using assorted channels, and that tremendous amount of information from these varied diverts can be progressively customized (Kopp, Mehra & Miller, 2013). Ongoing information examination enables firms to propose customized administrations involving exceptional maintenance and advancements to customers. What's more, these customized administrations help firms to dissociate loyal clients from new ones and to promote limited-time offers appropriately (Mehra, 2013). As indicated by Liebowitz (2013), personalization can build deals by 10 % or increasingly and give five to eight times the Return on investments of advertising uses. Bloomspot, in such manner, examined the information about the client's Visa, specifically, tracking the expenses of the most stable customers, offered them rewards through additional offers and advantages that also helped with expanding customer awareness (Miller, 2013). Wine.com accomplished a huge increment in their business utilizing customized email advertising (Zhao, 2013). Bikeberry.com is a case of a web based business firm that is presently utilizing Big Data Analytics (e.g., utilizing information from clients' perusing designs, login tallies, past buys) to send every client a custom fitted offer: this has prompted a business increment of 133 % and client on location engagement increment of around 200 % (Jao, 2013).

H1: Using Big Data tools is useful to enhance the content of personalized marketing.

H2: Ability to create personalized content can increase capacity of customers

H3: There is a significant difference in customers capacity between Big Data using and non-using companies

1. **Purchase Intention**

The purchase intention is the consumer's preference and desire to purchase a particular product or service. An important aspect in the purchase intention is the willingness of the consumer to purchase the goods after the evaluation. The choice of the product is influenced by a large number of factors, the intentions of consumers, along with external factors influence the final decision (Keller, 2001). Also, the purchase decision largely depends on group cohesion in the choice of brand (Witt & Bruce, 1972). Using information about the brand by other members of the group encourages consumers to buy the brand that other group members use (Witt, 1969). A significant focus on the members of consumers in the group affects other consumers in the group: the purchase of a certain brand (Moschis, 1976). Factors influencing the purchase intention are customer knowledge, packaging or design, consumer perception, the approval of celebrities, etc.

Consumer purchase intention depends on factors that influence how customers evaluate the product. These factors are based on what consumers feel and which perceived value they dedicate to any good or service (Keller, 2001). This evaluation of factors is main source of people's final decision on willingness to purchase the product. (Fishbein & Ajzen, 1975-1980) generated a theory explaining interconnection between customers' attitude and further intension to buy. Factors impacting the buy expectation are client learning, bundling or outline, buyer observation, the endorsement of celebrities, and so on. Big Data is a tool that can collect and analyze this info in real time what in further can flow into knowledge that can be concerned in company's strategy in order to enhance purchase intention.

According to studies by Satish and Peter (2004) and Rao and Monroe (1988), knowledge about the product is a key factor in purchase decision. Also, packaging is very important in making a purchasing decision, although the package has a dual purpose: on the one hand it's just an outlook, and on the other hand, attracting attention (Ann, 2008). There is also a claim that the properly selected packaging and design contribute to the reputation of the company in business and demonstrates the quality of the product (Dileep, 2006). For many, immensely important is the approval of celebrities. The purchase decision is also determined by perceived value, which implies a connection between the consumer and the product (Payneand Holt, 2001). The value of a product can be either tangible or intangible. However, the consumer decides to purchase a particular product relying on the knowledge of the product itself. It is also worth noting that the intention of the purchase affects positively the perceived value (Tun Zong et al., 1994).

H4: There is a significant difference in purchase intention from advertisements between frequent and non-frequent digital devices users

Data Gathering

Survey was distributed among marketing employees of companies that operates in Kazakhstan. A lot of companies use some internet platforms that connected to data analytical tools, such as Google AdWords or targeting in Facebook. Companies that optimize such tools automatically, but implicitly apply Big Data tools for personalization, since these applications use tools like Nos QL or Hadoop. Some Kazakhstani companies use basic functions of data analytical tools and collect personalized data about customers for marketing activities.

40 managers of Kazakhstani companies from oil, IT, business consulting industries were asked about their usage of digital tools such as Google AdWords, Social Media Marketing, and etc. that indirectly connected to Big Data. When companies install targeting to digital platforms they can be adjusted as Big Data users. Through these tools companies are able to see how people behave according to their pages and which products are under the high level of interest for potential or regular customer.

Questionnaire survey about purchase intention and attitude toward advertisements among frequent and non-frequent digital users was distributed among 72 respondents with different demographic and psychographic criteria. They have been asked to feel scale questionnaire about how they put an attention on advertising and how it comes to their purchase intention through these advertisements.

Data Processing and Analysis

2x2 contingency test through IBM SPSS analytical tool was chosen to find the association between usage of Big Data tools and availability to generate and information from collected customer's data. The chi-square test is chosen in the case of testing depending on frequency of distribution among sample participants and what association arises in the given distribution. This association is showing how usage of Big Data tools is significant to prepare personalized content for one-to-one marketing or marketing for specific target. The algorithm of association between Big Data and marketing recommendation system is tested through SPSS by Amatriain, Jaimes, Oliver, & Pujol (the year remained unknown). In their research they used more complicated test of relationship between to find coefficient and strangeness of this association between independent variables

To test hypothesis 2, linear regression is provided which explain the relationship between ability to create an advanced personalized content and capacity of clients of a company. Furthermore significant difference in this capacity is also tested by One-way ANOVA test in order to find the difference between Big Data users and non-Big Data users (Choi, J., Lee, H.J., Kim, H.W., 2017). In this study variables are represented as intention to purchase of clients from company's point of view. To find the significant difference between consumer behavior of frequent and non-frequent digital users One-way ANOVA is about to be implemented in this work. (Ismail, K. & Ishak, N., 2014; Choi, J., Lee, H.J., Kim, H.W., 2017). This difference will show the attitude in purchasing behavior between two groups depending on how close they are to their digital devices.

Analysis and implications

Table 1 – Table of crosstabulation between usage of Big Data tools and ability to create personalized content

Usage of Big Data tools * Ability to create personal content Crosstabulation

			Ability to create personal content		
			Able	Not able	Total
Usage of Big Data tools	Yes	Count	32a	3b	35
		Expected Count	28,9	6,1	35,0
		% within Usage of Big Data tools	91,4%	8,6%	100,0%
		% within Ability to create personal content	97,0%	42,9%	87,5%
		% of Total	80,0%	7,5%	87,5%
	No	Count	1a	4b	5
		Expected Count	4,1	,9	5,0
		% within Usage of Big Data tools	20,0%	80,0%	100,0%
		% within Ability to create personal content	3,0%	57,1%	12,5%
		% of Total	2,5%	10,0%	12,5%
Total		Count	33	7	40
		Expected Count	33,0	7,0	40,0
		% within Usage of Big Data tools	82,5%	17,5%	100,0%
		% within Ability to create personal content	100,0%	100,0%	100,0%
		% of Total	82,5%	17,5%	100,0%

Each subscript letter denotes a subset of Ability to create personal content categories whose column proportions do not differ significantly from each other at the ,05 level.

From analysis we got in this work we can see that most of sample use Big Data tools and numbers obviously show that Big Data usage has association to preparing personalized content. Usage of Big Data and ability to prepare personalized content was taken as two independent variables.

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Table 2 – Chi-Square test results

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Nominal by Nominal	Phi	,622			,000
	Cramer's V	,622			,000
Interval by Interval	Pearson's R	,622	,170	4,893	,000[c]
Ordinal by Ordinal	Spearman Correlation	,622	,170	4,893	,000[c]
N of Valid Cases		40			

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.
c. Based on normal approximation.

Chi-square test showed 15, 461 value that is showing strong association between each other and degree of freedom as 1. 2-sided significance level of chi-square test shows that two independent variables have significant relationship between each other.

Table 3 – Asymptotic symmetric measures test results

Symmetric Measures

		Value	Asymptotic Standardized Error[a]	Approximate T[b]	Approximate Significance
Nominal by Nominal	Phi	,622			,000
	Cramer's V	,622			,000
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N of Valid Cases		40			

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.
c. Based on normal approximation.

From symmetric measure approximate significance is equal to 0.0 with standardized error 0,17. From this test we can see the significant relationship between usage of Big Data and ability to create personalized marketing content and this relationship approve hypothesis developed in this work.

Table 4 – Descriptive Statistics of 40 surveyed Kazakhstani companies

Descriptive Statistics

	Mean	Std. Deviation	N
Amount of sales	3,2500	1,10361	40
Ability to create personal content	1,2000	,40510	40

Table 5 – Correlations between ability to create personal content and amount of sales they make

Correlations

		Amount of sales	Ability to create personal content
Pearson Correlation	Amount of sales	1,000	-,459
	Ability to create personal content	-,459	1,000
Sig. (1-tailed)	Amount of sales	.	,001
	Ability to create personal content	,001	.
N	Amount of sales	40	40
	Ability to create personal content	40	40

Table 6 – One way ANOVA test of difference in customers capacity between companies that able and not able to personalize content.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10,000	1	10,000	10,133	,003[b]
	Residual	37,500	38	,987		
	Total	47,500	39			

a. Dependent Variable: Amount of sales

b. Predictors: (Constant), Ability to create personal content

Table 7 – Model summary of linear regression between ability to personalize content and capacity of customers

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,459[a]	,211	,190	,99340	,211	10,133	1	38	,003

a. Predictors: (Constant), Ability to create personal content

Linear regression test (Table 5) shows that the existing relationship between success of campaign personalization and capacity of clients that a company has. Estimated significance level is 0,001 which is less than 0,005 among 40 companies. This shows that H2 is also supported and there is a significant relationship between ability to personalize content and number of client. ANOVA test (Table 6) shows that there is a significant difference (p= 0,003<0,005, F=10,133) in customers capacity between companies that able and not able to personalize marketing content.

Table 8 – One-way ANOVA test representing the difference in customers capacity between users and non-users of Big Data

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12,014	1	12,014	12,866	,001[b]
	Residual	35,486	38	,934		
	Total	47,500	39			

a. Dependent Variable: Amount of sales

b. Predictors: (Constant), Usage of Big Data tools

Testing difference in customers capacity between Big Data using and non-using companies we see that p=0,001<0,005 and F=12,866, so H3 is also supported and we can accept that there is a significant difference in number of customers between Big Data using and non-using companies.

Table 9 – Descriptive statistics of people responding about their behavior toward digital advertising

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
Attention on advertising	Yes	50	3,5800	,97080	,13729	3,3041	3,8559	2,00	5,00
	No	22	2,6364	1,21677	,25942	2,0969	3,1758	1,00	5,00
	Total	72	3,2917	1,13134	,13333	3,0258	3,5575	1,00	5,00
Attention on ads in SM and SE	Yes	50	4,1400	1,06924	,15121	3,8361	4,4439	2,00	5,00
	No	22	3,1364	,94089	,20060	2,7192	3,5535	1,00	5,00
	Total	72	3,8333	1,12588	,13269	3,5688	4,0979	1,00	5,00
Match with needs and wants	Yes	50	3,8600	1,17820	,16662	3,5252	4,1948	1,00	5,00
	No	22	2,3182	,83873	,17882	1,9463	2,6901	1,00	4,00
	Total	72	3,3889	1,29523	,15264	3,0845	3,6933	1,00	5,00
Match with previous search	Yes	50	3,7400	1,10306	,15600	3,4265	4,0535	1,00	5,00
	No	22	2,2727	1,24142	,26467	1,7223	2,8231	1,00	4,00
	Total	72	3,2917	1,32620	,15629	2,9800	3,6033	1,00	5,00
Purchase intention	Yes	50	3,7800	1,09339	,15463	3,4693	4,0907	1,00	5,00
	No	22	2,9091	1,26901	,27055	2,3464	3,4717	1,00	5,00
	Total	72	3,5139	1,21020	,14262	3,2295	3,7983	1,00	5,00
Purchase completence	Yes	50	3,4000	1,16058	,16413	3,0702	3,7298	1,00	5,00
	No	22	2,4091	1,25960	,26855	1,8506	2,9676	1,00	5,00
	Total	72	3,0972	1,26891	,14954	2,7990	3,3954	1,00	5,00

To test H4, we implemented One-way ANOVA test to find difference in purchase intention which is coming from advertisements between frequent and non-frequent digital device users. In this term we have results of p=0,004 which is less than 0,005 and F-8,779. From this perspective H4 is also supported and there is a significant difference in purchase intention of frequent and non-frequent digital users.

Discussion and Conclusion

Table 10 – One-way ANOVA test of difference of attitude toward advertising between frequent and non-frequent digital users

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Attention on advertising	Between Groups	13,604	1	13,604	12,324	,001
	Within Groups	77,271	70	1,104		
	Total	90,875	71			
Attention on ads in SM and SE	Between Groups	15,389	1	15,389	14,438	,000
	Within Groups	74,611	70	1,066		
	Total	90,000	71			
Match with needs and wants	Between Groups	36,318	1	36,318	30,707	,000
	Within Groups	82,793	70	1,183		
	Total	119,111	71			
Match with previous search	Between Groups	32,891	1	32,891	25,030	,000
	Within Groups	91,984	70	1,314		
	Total	124,875	71			
Purchase intention	Between Groups	11,588	1	11,588	8,779	,004
	Within Groups	92,398	70	1,320		
	Total	103,986	71			
Purchase completence	Between Groups	15,001	1	15,001	10,573	,002
	Within Groups	99,318	70	1,419		
	Total	114,319	71			

Previous studies have described the way how customers are willing to come to purchase of product. Interpretation of all findings about Big Data tools and customer experience prompted on the ability of educating customer's behavior through these tools. Sometimes customers look for products and even don't understand their own needs and wants and in massive market behave with high level of frequently while making purchase decision. Also, people don't know what market can suggest people to buy in order to solve a particular problem or satisfy a specific need. That creates tunnel vision for companies and it cannot indicate what kind of marketing activities should be accomplished. In this term Big Data tools can automatically process information collected from every digital activity of potential customers and create the channel between company and the customer. Using Big Data tools efficiently create the channel of indirect communication between customers and companies about things that are able on the market and companies educating needs and wants can adjust promotional activities for specific segment of consumers or even for individual that seeking for specific product or service.

Since all hypotheses are supported significant notification must go around companies that work in B2B and B2C markets. Implementing Big Data as a marketing tool can helpfully strengthen marketing activities by collecting and absorbing information about clients and create personalized content. This content will have an effect on capacity of customers that company has and it depends on how the information collected and analyzed by Big Data will be directed and used. From provided (ANOVA) test of H3 we can see that the difference in the number of customers present according to presence of Big Data as a tool in operations. Which showed that companies will have more clients when Big Data is applied.

In the case of test of H4 (table 10), the direction from attention to purchase intention is constructed. The significant difference exists in all concepts which have been applied as components on the way to purchase intention of customers. During this test, the difference between how advertising matches with needs and wants or previous searches of customers are present, digital users see more advertising through their digital devices because these advertisements comes around through recommendation systems supported by Big Data. In the case of purchase completion significance is also present, but without considering factors of product and industry, purchase completion is also constructed from different factors which are not applied and tested in this work.

Big Data tool users create a tunnel through which customers automatically receive information from company according to what they were searching before, or where they are located right now. Companies set up promotional content through these Big Data tools to reach customers that are mostly interested about the product and can enhance and narrow down the content to persona level. That content will be structured dependent on information constructed from absorbed and distilled data about customer's current location, needs or wants, conditions or other situations. Analyzed data formulate the way in which company can reach particular segments by strengthened content with consideration of their preferences and ways that can catch an attention of segments' participants.

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Резюме

В данной работе описывается применение программного обеспечения по сбору данных в маркетинге. Также в данной работе упомянута проблема с "Туннельным видением" которая рассматривается, как очень прогрессивная, которая исходит из-за некачественной информации о клиентах, которые компании собирают на конкурентном рынке. Применение новых программных обеспечений описаны как инструменты, способные усилить операции направленные на расширение данных о клиентах, с целью применения необходимых маркетинговых действий.

Түйін

Осы жұмыста маркетингтік деректерді жинауға арналған бағдарламалық жасақтаманың пайдалануы сипатталады. Сондай-ақ, осы жұмыста бәсекелестік нарықта жиналатын тұтынушылар жайлы сапасыз ақпаратқа негізделген, өте прогрессивті деп саналатын «Туннельное видение» мәселесі көрсетілген. Жаңа бағдарламалық жасақтаманы қолдану қажетті маркетингтік шараларды қолдану үшін клиенттердің деректерін кеңейтуге бағытталған операцияларды күшейтетін құралдар ретінде сипатталады.

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