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Effects of Pros and Cons of Applying Big Data Analytics to Consumers' Responses in an E-Commerce Context

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Abstract: The era of Big Data analytics has begun in most industries within developed countries. This new analytics tool has raised motivation for experts and researchers to study its impacts to business values and challenges. However, studies which help to understand customers' views and their behavior towards the applications of Big Data analytics are lacking. This research aims to explore and determine the pros and cons of applying Big Data analytics that affects customers' responses in an e-commerce environment. Data analyses were conducted in a sample of 273 respondents from Vietnam. The findings found that information search, recommendation system, dynamic pricing, and customer services had significant positive effects on customers' responses. Privacy and security, shopping addiction, and group influences were found to have significant negative effects on customers' responses. Customers' responses were measured at intention and behavior stages. Moreover, positive and negative effects simultaneously presented significant effect on customers' responses. Each dimension of positive and negative factors had different significant impacts on customers' intention and behavior. Specifically, information search had a significant influence on customers' intention and improved customers' behavior. Shopping addiction had a drastic change from intention to behavior compared to group influences and privacy and security. This study contributes to improve understanding of customers' responses under big data era. This could play an important role to develop sustainable consumers market. E-vendors can rely on Big Data analytics but over usage may have some negative applications.

Keywords: e-commerce; Big Data analytics; positive and negative factors; customers' responses

1. Introduction

With increasing advancement of Internet technology, increasing amounts of data are streaming into contemporary organizations. Data are getting bigger and more complicated due to the continuous generation of data from many devices and sources such as mobile phones, personal computers, government records, healthcare records, and social media. An International Data Cooperation report estimated that the world would generate 1.8 zettabytes of data (1.8×10^{21} bytes) by 2011 [1]. By 2020, this figure will grow up to over 35 zettabytes. The Big Data era has arrived. Why are researchers and practitioners interested in understanding the impacts of Big Data analytics? The simple answer of this critical question is that Big Data enables to bring potential applications. Big Data analytics (BDA) applications can help organizations predict the unemployment rate, stimulate economic growth, and provide the future trend for professional investors and other sectors. In health care, big data could help to predict impact trends of certain diseases. One of the most conspicuous examples of Big Data for health care is Google Flu Trend (GFT). In 2009, Google used Big Data to analyze and predict trends influence, a spread of H1N1 flu virus. The trend which Google has drawn from the search keywords related to the H1N1 has been proven to be very close to the results from flu independent warning system Sentinel GP and Health Statistics launched. The GFT program was designed to provide real-time monitoring of flu cases around the world based on Google searches that match terms for flu related activity.

Big Data is generating remarkable attention worldwide with various definitions of Big Data. Big Data is a dataset with a size that can be captured, communicated, aggregated, stored, and analyzed [2]. Another definition is that Big Data is generated from an increasing plurality of sources including Internet clicks, mobile transactions, user generated content, and social media as well as purposefully generated content through sensor networks or business transactions such as customer information and purchase transactions [3]. Big Data owns distinctive characteristics (volume, variety, velocity, veracity, and value) that can be easily distinguished from the traditional form of data used in analytics.

Each industry moves a step closer to understanding the world of Big Data from how it is being applied in solving problems. Most industries are still estimating whether there is value in implementing big data, while some other industries have already applied Big Data analytics.

Applications of Big Data were shown in top ten industries such as banking and securities, communications, media and entertainment, healthcare providers, healthcare providers, education, manufacturing and natural resources, government, insurance, retail and wholesale trade, transportation, energy and utilities. Even though Big Data faces specific challenges, its implementation has been practiced by industries in these sectors.

The activity of retailing and wholesaling is part of our economy as well as daily life. Consumer and business markets buy products and services everyday according to their needs and preference. The retail and wholesale sectors contribute significantly to the countries national economy. In today's competitive and complex business world, the company needs to rely on the data-structured and new type of data-unstructured or semi-structured to back up their decisions. BDA can bring benefits for e-vendors by improving market transaction cost efficiency (e.g., buyer–seller transaction online), managerial transaction cost efficiency (e.g., process efficiency) and time cost efficiency. Specifically within the e-commerce context, Big Data enables merchants to track individual user's behavior and determine the most effective ways to convert one-time customers into regular customers. The injection of big data analytics into a company's value chain equates to 5–6% higher productivity compared to their competitors [4]. Recent studies are focusing on positive mechanisms of applying Big Data analytics with little attention to the negative effects of applying Big Data analytics such as privacy and security [5], shopping addiction [6] and group influences [7]. However, the positives and negatives of applying big data analytics on customers' responses have not been reported.

Before 2008, three models of consumers' behavior were discovered; the customers intended to consume more products. In 2008, the global economic and financial crisis that occurred all over the world has led customers to think twice before buying. Consequently, customers were purchasing less and their behavior became defensive. Today, customers face massive and diverse information. Therefore, the opportunity cost for decision process is more complex and their behavior became unpredictable. It requires a new method to understand customers' behavior and Big Data analytics can be a potential method. Many previous studies reported that the impact of Big Data analytics to business values and business challenges [8,9]. However, it is lacking research on customers' views, to see how customers think about the application of Big Data analytics for online shopping. Thus, the research on customers' responses towards the influence of pros and cons in applying Big Data analytics is becoming an advanced trend in marketing strategy.

From the marketing perspective, the AIDA model is explored and used to measure the responses of customers by four stages: attention, interest, desire and action [10,11]. The AIDA model was developed to represent the four stages that an e-vendor takes their customers in the selling process. This model illustrates that the buyers as passing through attention, interest, desire and action. E-vendors have to firstly get the customer's attention and then push their interest in the product or service. Strong interest should create desire to have a product or service usage. The action in the AIDA model depicts customer getting to make a purchase and closing the sale. Based on the AIDA model, this study explores consumer responses by two stages: Intention and Behavior.

This research focuses on exploring and determining the positive and negative factors of applying Big Data analytics influence on customers' responses in B2C e-commerce environments using application of Big Data analytics. Through analysis, the influencing factors of applying Big Data analytics can help enterprises to adjust strategy and meet consumer demand when they apply BDA. Customers also can understand themselves under Big Data era.

2. Theoretical Background and Hypotheses Development

The literature review section includes the following: (Section 2.1) concept of Big Data and its characteristics, (Section 2.2) positive factor of applying Big Data analytics, and (Section 2.3) negative factor of applying Big Data analytics.

2.1. Big Data and Its Characteristics

Big Data is a collection of massive and complex datasets and data volume that includes huge quantities of data, data management capabilities, social media analytics, and real-time data. Big Data can come from structured and unstructured data with five V as distinct characteristics (Volume, Velocity, Value, Variety and Veracity) [12].

The changes in consumer behavior had strong influences on all enterprises throughout time. A decision moment occurred in the 1970s when a significant macroeconomic change affected the law of supply and demand. Until 1960, the economic perspective of consumer behavior and the models relied on the assumption that all consumers were always rational in their purchases, so they will always purchase the product which brings the higher satisfaction. Before 1979, scientists developed three models (Economic Model, Learning Model, and Psychoanalytic and Sociological Model) [13]. During that time, consumers had conservative behavior on buying the same products. Moreover, consumer behavior is an emergent phenomenon that has evolved along with human development. This diversification of needs is the main cause that stimulated the researchers to study the consumer behavior. In 2008, the economic and financial crisis that spread all over the world led consumers to think twice before buying a product. Consumers were buying less products meaning their behavior tend towards a defensive one. Online marketing began to take a role in purchases. People started to use the Internet to order and compare the prices and characteristics of interested products. At present, customers face diverse offers, which leads customers' decision process to be more complicated and their behavior become unpredictable. Thus, new techniques were developed in order to predict consumers' behavior. One of them being is the big data analytics [14].

While customers can tell what they think, researchers can tell what the customers actually purchase. Data on actual consumer behavior and experiences are now available to be measured and analyzed. Big Data analytics was used and developed in order to understand more of the customer's behavior. However, using big data in doing business especially e-commerce has advantages and disadvantage as well.

2.2. Positive Factor of Applying Big Data Analytics

Positive factor of applying Big Data analytics application includes offering information search, recommendation system, dynamic pricing and customer service to interact with the community member. By collecting different data in Big Data era such as geographic distribution, emotional tendencies, customer behavior on shopping as well as social connection, hobbies, companies can achieve demand orientation preference orientation, relationship orientation, and other ways to satisfy customers. E-commerce vendors used information and communication technologies through using different data mining techniques to provide personalized services to customers, redesign the website to provide better services [15]. Akter [8] indicated that e-vendors apply Big Data analytics to create personalized offers, set dynamic price, and offer the right channel to provide consumer value. Applying Big Data analytics by offering virtual shopping experience, a more direct experience of personalized products will stimulate consumers desire to buy products [16]. All these four positive applications of positive factor above will help catch customers' intention, bring good customers' behavior and finally lead them take action to buy a product or service from e-vendors. Accordingly, the following hypothesis is suggested:

Hypothesis 1 (H_1). *Positive factor of applying Big Data analytics is positively associated with customers' responses.*

2.2.1. Information Search

Emotionally driven consumers are easy to induce their purchase desire and demand by network information. The speed and convenience of gathering online information is one of the perceived values for customers when they shop online. A website using Big Data analytics tool can filter and browse a large number of data to customer information. Text miner technology is used to solve within the web and text search and note the relevance of history with libraries, catalogs, and coincidences. Big Data is all about relevancy and offering the right products or services to the right person for the right price via the right channel at the right time. For example, Google personalizes its search results based on users profile and Amazon offers different homepages with different products on offer to almost every visitor. It comes back to completely knowing your customer by combining different data sources to really know what they are looking for.

Information search indicates that information quality and searching service quality. Information quality is a measure of value perceived by output provided by a website. Information characteristics, such as update, useful, detailed, accurate, and completed have been viewed as important components of information quality [17]. Searching service quality can be defined as overall customer evaluations regarding quality of searching service as quickly responsiveness [18], suitable and realistic. Based on customer's choice and action, online retailer using Big Data analytics can provide real-time services to customers. This action may become one of the sources of competitive advantages to gain customer's satisfaction [19].

2.2.2. Recommendation System

Recommendation systems are operated by famous sites such as Amazon, eBay, Netflix, Monster, and other Retail stores where everything is recommended. This involves a relationship between e-vendors and buyers whereby the buyers provide their information such as hobbies and preferences, while the e-vendors offer a recommendation fitting their needs, thus benefiting both. Details are given on basic principles behind recommendation systems: user-based collaborative filtering which used similarities in user rankings to predict their interests and item-based collaborative filtering as points in a space of items. Collaborative filtering systems use customer interactions and product information with ignoring other factors to make suggestions [20,21]. Recommendation system has chosen some algorithms to use in recommendation model such as K-nearest neighbor is a collaborative filter based on measures of association between items or users; Cold starting recommends typical products popular across your customer base to new website visitors; Association rules automatically recommend related items to those you browse or place in your cart; Clustering is an algorithm to group similar users or items together to streamline analysis of massive data matrices; and slope one estimates preferences for new items based on average difference in preference value (ratings) between a new item and the other items a user prefers.

A recommendation system based on the customer's purchase behavior can evaluate commodity information, study the interests of customers, product matching and recommend customers substitute or complementary products. Recommender systems help individuals to identify items that might be of interest to them from a large collection of items by aggregating inputs from all individuals [22]. In these systems, recommendations are usually made based on a mixture of past purchasing or browsing behavior, characteristics of the items being considered, and demographic and personal preference information of shoppers [23]. Chevalier and Mayzlin [24] indicated that other Internet consumers' product recommendations had an impact on consumer purchasing behavior at online retailer sites.

E-commerce recommendation system can help consumers to choose favorite products that can be implemented in real networks, such as Amazon, Taobao, Google and other websites to promote the sale [25].

2.2.3. Dynamic Pricing

Dynamic pricing is an individual-level price discrimination strategy where prices are charged according to customer, location, product, or time [26]. Dynamic pricing, often referred to in economic terms as individual-level price discrimination, has become much more common with increased prevalence of Internet marketing. Dynamic pricing is mostly defined as the buying and selling of products in markets where prices are free to adjust in responses to supply and demand conditions at the individual transaction level. Thus, dynamic pricing can attract most retailers with the ability to use the newly available information to individually set prices based on a given customer's willingness to pay [27].

The purpose of dynamic pricing is to maximize the seller's profit by charging consumers with the highest prices each consumer is willing to pay by manipulating the magnitude and the temporal proximity of price differences they will employ. Consumers' reactions to this pricing scheme strategy will have a significant impact on their satisfaction with purchases and their subsequent behavioral intentions. For example, Amazon normally changes the price of items sold on its website on a daily, weekly, or monthly basis by 5%, 10% or 15%. Dynamic pricing practices by sellers in responses to segment and individual level differences have been made more feasible as online customers' behavior increases [28,29].

Consistent with the recommendations of Jiang and Benbasat [30], the present research investigates the effects of various dynamic pricing contexts and can be consider as an additional transaction characteristics. Economic theory argues that dynamic pricing (i.e., individual-level price discrimination) is naturally good for the profitability of the firm because it allows the firm to capture a larger share of the consumer surplus. However, evidence from recent retail experiments with Internet based dynamic pricing suggests that consumers react strongly against this practice.

2.2.4. Customer Services

Providing high-quality customer service is an important key to keep the customers happy. Big Data enables you to drastically improve your services. Using deep data analytics, you can optimize your customer service resulting in happier customers. Some customers may not only complain of products or services through the official channels offered by website, but may also go social about their groups. You need to have data of such customers and exercise extra caution so that complaints of such customers are addressed double-quick. Big Data is used to enhance business processes. Retailers can optimize their stock based on predictions from web search trends, customer behavior and weather forecasts. One special application for business process is the analytics in supply chain or delivery route. Based on geographic position and radio frequency identification, sensors are used to track goods or delivery vehicles. This process enables customers to track their orders. From that, the customer services can be improved and increase customer satisfaction.

Amazon used Big Data analytics to save what customers have placed inside their virtual shopping cart. These items have recently viewed or take a purchasing action in the past. The technique used here is item to item collaborative filtering. Another application is virtual presence which enables online shoppers to interact with shopping experience. Unlike traditional online retailing, online shopping has shopping information being suggested to consumers through several channels including product trial, product offering or services. Virtual reality or virtual product experience lets customers to interact with online products and experience a much wider range of those products' characteristics [31]. Earlier exploratory studies have recommended that virtual reality has the potential to enhance the consumers' product knowledge and brand attitude including enhancement in their purchase intentions [31,32].

A review of customer is a feedback of a product or service made by consumer who has purchased. It evaluates the product or service quality and give comments on the website instead of professional reviews. Interested customers can see the feedback of previous customers who has interacted with the website before. This service can guarantee shoppers of products trustworthiness. They can also inspire other customers to share their thoughts about the products being sold.

2.3. Negative Factor of Applying Big Data Analytics

Besides the benefits of applying BDA bringing customer values, applying BDA may give customers some negative effects. Detailed descriptions are presented in the following subsections.

2.3.1. Privacy and Data Security

The privacy of Big Data is another huge concern and one that increases in the context of Big Data. Due to the distinctive characteristics of Big Data in the e-commerce environment, it can relate to privacy and security concern. The high volume and concentration of data makes a more appealing target for hackers. Additionally, higher data volume increases the probability that the data files and documents may contain inherently valuable and sensitive information. Data for the purpose of Big Data analytics are thus a potential goldmine for cyber criminals [33].

Recently, studies indicated that there is an increasing consumer concern over privacy in the context of real time behavioral advertising and tacking technologies such as cookies [34]. The Internet advertising firms Double Click and Avenue A, software firm Intuit and others have faced lawsuits for using cookies to target advertising.

A high diversity of Big Data information lead to organizations lacking the ability to manage and solve these data, and third parties have opportunities to access data. They may not comply with data protection regulations.

2.3.2. Shopping Addiction

Shopping addiction is a form of frequent and under recognized behavioral addiction. Behavioral addiction is individuals' failure to perceive the strength of post-addiction cravings and a failure to control desire [6]. For shopping addicts, shopping becomes uncontrolled and they not only buy items they need or they like [35], but also really spend their money and are anxious to miss a good opportunity to buy something. These products may not be used after purchase. Using the applications of Big Data analytics, the website can recommend customers other products as substitute or complementary products. This application is very useful for customers with products they want to buy but this is also harmful for customers. They will have to spend more time to review more products to make decision. It also recommends other complementary product which customer feels they need to purchase to increase the purchased products. For example, a customer has purchased a very beautiful pink dress and the website recommends her relevant bags or shoes that are suitable with the dress. They are preferred to combine together to give customer satisfaction. Customer has to spend time and money to buy these complementary products because of a good opportunity to buy them, even with less money. Shopping addictions are found to show under two basic dimensions: tendency to spend and post-purchase feeling [35].

2.3.3. Group Influences

Consumers are influenced by groups they believe they are part of or aspire to be part of. Group influences to some extent can make a customer change their intention by review group thinking. Sometimes, consumers keep away from brands they believe would put them into a group they do not want to be included in. People buy things to help form and express their self-concept and their connections with like-minded people. An individual selection can change under social networks affected by group emotion. Consumers post their feedback after purchased products or services on the website. Feedback could not be considered as forged online marketing [36]. It has strong perception in human mind for a powerful and social communication. Review of customers is the way of sharing thoughts, ideas, beliefs and experiences among customers. The mix of positive and negative reviews makes consumers take time to read them and will influence customers' decision. Online shoppers are very much influenced by group community, and a larger percentage of them are dependent group when making decisions to purchase products [37]. Negative groups influence negatively more strongly than positive groups influence positively [36].

Negative factors include privacy and security problem, shopping addiction and group influences. Customers feel uncomfortable and embarrassed when they think that e-vendors know more about them [33]. Guangting [16] said that analyzing Big Data has negative impact on the consumers' willingness. Negative factors will decrease customers' intention and stimulate their negative behavior, finally drive them to refuse taking action to buy products or services. As discussed above, we propose the following hypothesis:

Hypothesis 2 (H_2). *Negative factor of applying Big Data analytics is negatively associated with customers' responses.*

2.3.4. Behavior Consumer Responses Hierarchy Models

AIDA model is a basic movement of marketing and advertisement resulted from perception of customers. A, I, D, A is an abbreviation for Attention, Interest, Desire and Action. Website's information should be able to attract the group's attention, raise customer's interest, convince customers that they want and desire the products or services and finally lead customers forward taking action or purchase [38]. In detail, the model includes four stages: First step is attracting customer's attention to mean that website need to attract customer's attention and want to know more detail about the product before selling a product or service. There are many ways to catch attention. With website using Big Data analytics, it can be done by positive applications such as quick and good searching results, very attractive recommendations or promotion messages. Second step is creating interest in the client. It means indicating features and benefits of products so customers become interested in products or services of e-vendor. Third step is creating enthusiasm in customer, which is very important. The e-vendors should know how customers think about the provided information which able convinces customers and customers intend to supply of goods or keep interaction with the website. The last step is to end the purchase process that customers will have action to buy product and introduce this product or website to others. AIDA model proposes two roles: the role of information and the role of persuader. The role of information is guiding a consumer's selection and consumers would be under impact of information to recall and evaluate information. The role of persuader is that advertising can persuade customers to take buying action. In this study, based on AIDA model, customers' responses can be measured into intention and behavior stages. The combination of attention and interest stages is become to customer's intention stage. The combination of desire and action stages is become to customers' behavior stage.

The structure of the proposed model is shown in Figure 1.

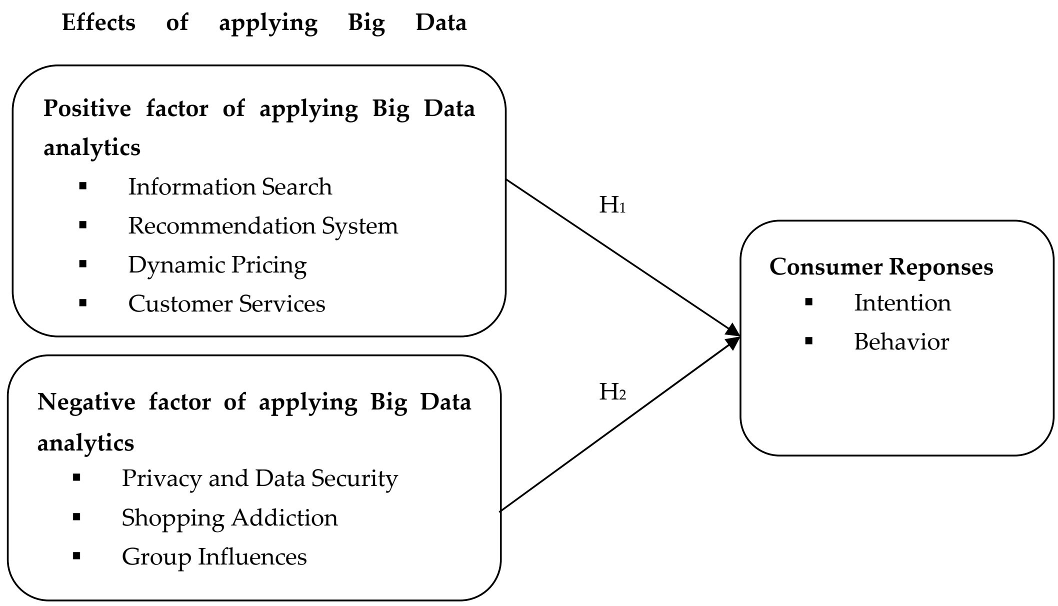

Figure 1. The research model.

3. Research Methodology

3.1. Pilot Test

A pre-test was conducted to ensure reliability and validity of the adapted scales. Fifty respondents (n = 50) were invited to participate in the pre-test study. Their feedbacks were analyzed in order to adjust the questionnaire. Cronbach's alpha (α) will be used to examine the reliability analysis. These coefficients will be exploited to test the internal consistence of the variables. If Cronbach's α is greater than 0.7, it means high reliability. If the Cronbach's α ranges between 0.5 and 0.7, it means the internal consistency of the variable should be accepted. Otherwise, if the item has Cronbach's α coefficient under 0.35 and Cronbach's α if item deleted is higher than total Cronbach's α, then it should be deleted [39]. On the other hand, these participants were pre-tested with the questionnaire according to its understanding and clarity. Changes in wording were made in the questionnaire on the pre-test.

After doing pre-test, one item of privacy and data security was deleted because the Cronbach' α if item deleted was higher than total Cronbach's α of variable.

3.2. Sample Size and Data Collection Procedure

3.2.1. Sample Size

According to Gravetter [40], a sample is a set of individuals selected from a population and is usually intended to represent the population in research study. According to Kline [41], although there are no absolute standards in the literature about the relation between sample size and path model complexity, the following recommendations are offered: a desirable goal is to have the ratio of the number of cases to the number of free parameters be 20:1; a 10:1 ratio, however, may be a more realistic target. Thus, based on this research path model, this study should have a minimum sample size of 220 cases. Therefore, the research used more than 220 respondents.

Along with the rapid development of the Internet, Asia is becoming one of the e-commerce markets with the fastest growth in the world. Besides China, Korea, Japan, China and the others, e-commerce in Vietnam has grown rapidly, resulting in Vietnamese consumers now gradually changing their habit of online shopping. According to the Internet World Stats 2011, Vietnam has more than 30 million Internet users, representing more than 30% of the nationwide population. Vietnam has become a country with the fastest growing Internet market in Southeast Asia. It has become a more dynamic and favorable market for e-commerce. For those reasons, Vietnam depicts a special case being chosen to in this study.

The survey data were collected from a sample of students, since college students have had experience in using the Internet. The feasibility of using students as sample has been demonstrated in many previous studies [42–44]. Besides, according to a report [45], students are the key convenient shopper and become potential customers of e-commerce market.

A total of 350 subjects participated in this study during 15–30 December 2016. About 20 questionnaires were not fully completed and after doing explore data, 57 respondents were outliers. They were removed. The remaining 273 samples were used for analysis. Table 1 presents the demographics characteristics of the respondents. Because none of the demographic characteristics had a significant effect on the results, they were not investigated further.

Table 1. Demographic descriptive (n = 273).

Variables	Valid	Frequency	Percent (%)
Gender	Male	103	37.7
	Female	170	62.3
How many times per month have you accessed in e-commerce website?	Not at all	47	17.2
	1–2 times	79	28.9
	3–4 times	57	20.9
	More than 4 times	90	33.0
Kind of product was chosen for survey	Fashion item	140	51.3
	Electronics item	133	48.7

3.2.2. Data Collection Procedure

The study was conducted in the computer center of Thai Nguyen University, Vietnam for the purpose of understanding the research and minimizing interference during the survey participation. The respondents were asked to navigate to the Amazon website (www.amazon.com) which is one of the famous websites using Big Data analytics application. This action is required to be performed at least two times on computer, going through the procedure of buying one of two products on the website, but not actually purchasing the item. This ensured that the respondents have interaction experience with the website applying Big Data analytics. After that, the respondents were required to complete the survey. Based on the report of Vietnam e-commerce [45–47] in 2013, 2014 and 2015, two products, fashion items and electronics, are the best sellers of e-commerce market in Vietnam.

3.3. Measurement

The questionnaire used in this research was designed according to related literature, creating new measurement, and survey users' and experts' opinions. After a draft was completed, a pilot test was performed on experts and users familiar with e-commerce in order to ensure the content validity of the survey. The modifying items and wordings with ambiguous expressions were done. The questionnaire was composed of two sections. The main section measures the respondents' perception of each construct in research model. In another section, several demographic characteristics were assessed: gender, experiences and which product was chosen to interact with website. The research construction and items included in the questionnaire are presented in Table 2. The questionnaire used a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

Table 2. Constructs and items included in the questionnaire.

Construct	Variable	Items	Measurement	References
Positive factor	Information Search (IS)	IS1	I am able to search the useful information in the e-shopping website.	[48]
		IS2	The information I search in the e-shopping site are detailed and completed.	
		IS3	The result is provided quickly and fit to my need.	
		IS4	Search result provided by shopping website is very realistic.	
	Recommendation System (RS)	RS1	Shopping website can recommend substitute goods for the product I want to buy.	[48]
		RS2	Shopping website can recommend complementary goods for the product I want to buy.	
		RS3	Shopping website can recommend for you some product may be you like or best sellers of website.	
		RS4	I believe that the recommendation information is an act of kindness.	
	Dynamic Pricing (PD)	PD1	Providing different prices for individual customer at the same time.	New measurement
		PD2	Offer different prices at different time.	
		PD3	Providing different prices with different substitute products.	
		PD4	Providing different prices with different conditions on the same product.	
	Customer Services (CS)	CS1	The website provides channel to support customers.	[48]
		CS2	I expect that I am able to track my order.	
		CS3	The shopping website which provides virtual experience can let me choose more suitable goods.	
		CS4	I can refer to the reviews of customers who bought the products before.	
Negative factor	Privacy and data Security (PS)	PS1	Attracting a great deal of attention from cybercriminals	New measurement
		PS2	Customer's personal information will be stolen.	
		PS3	My information about payment method will be stolen.	
	Shopping Addiction (SA)	SA1	Spending a lot of time to review products.	[35]
		SA2	I have often bought a product that I did not need, while knowing that I had very little money left.	
		SA3	As soon as I enter a shopping website, I have an irresistible urge to go into a shop and buy something.	
		SA4	I have felt somewhat guilty after buying a product, because it seemed unreasonable.	
	Group Influences (GI)	GI1	When I buy a product online, the reviews presented on the website are helpful for my decision making.	[37]
		GI2	Reviews posted on the website affect my purchase decision.	
		GI3	Reviewers' rating of usefulness of the review affects my purchase decision.	
		GI4	Popularity of web site that present the reviews affect my purchase decision.	
Customer Responses (CR)	Customer Intention (CI)	CAI1	The applications on website catches my attention.	[10,11]
		CAI2	I had trying to read that information.	
		CI1	Continuously pay attention.	
		CI2	I want to get more information.	
	Customer Behavior (CB)	CD1	I want to buy the product.	
		CD2	I will continue to use this webpage for shopping.	
		CAC1	I will have action to buy.	
		CAC2	I will introduce this webpage to my friends and family.	

3.4. Statistical Data Analyses

The statistical package for social sciences (SPSS 22.0) and analysis of moment structures (AMOS 22.0) software were used to analyze data. SPSS 22.0 was used to test the reliability of measurement items, exploratory factor analysis (EFA), descriptive analysis, and regression analysis. Confirmatory factor analysis (CFA) and structural equation model (SEM) in AMOS 22.0 were used to measure for the reliability, convergent and divergent validity and to test hypothesized relationships.

To test the internal consistency of the indicators of each factor, the most common method is calculating the Cronbach's α value [49]. In this study, Cronbach's α were calculated for internal validity, the Cronbach's α value of all variables ranged from 0.827 to 0.880 which are higher than recommended value 0.700 [39]. Therefore, all variables were internally consistent and reliable to conduct in this study.

In Table 3, it has been found that several variables are highly correlated. The exploratory factor analysis (EFA) was performed to solve this problem by determining the latent constructs. The value of KMO (Kaiser–Meyer–Olkin) value is found to be 0.825 and significant value p <0.05 indicated that the dataset is reasonably good for doing factor analysis. For EFA, the principle component analysis, varimax rotation, Eigen value greater than 1 and factor loadings greater than 0.4 were used [50]. We observe that all seven indicators are scattered over two factors with Eigen values greater than 1 and can explain 82.38% variance. The factor loadings can easily identify groups and provide names for each factor. As suggested by results of EFA (Table 4), all the variables influence to customers' responses was divided into two factors. Information search, recommendation system, dynamic pricing and customer services were integrated into the factor named positive factor, whereas, privacy and security, shopping addiction and group influence were composed into factor named negative factor.

Table 3. Correlation among variables.

	Mean	Std	IS	RS	PD	CS	PS	SA	GI	CI	CB
IS—Information Search	5.138	0.872	1								
RS—Recommendation System	5.217	0.858	0.871 **	1							
PD—Dynamic Pricing	5.293	0.871	0.807 **	0.819 **	1						
CS—Customer Services	5.202	0.883	0.806 **	0.818 **	0.802 **	1					
PS—Privacy and Security	3.651	1.035	−0.157 **	−0.141 *	−0.133 *	−0.108	1				
SA—Shopping Addiction	3.823	0.970	−0.110	−0.104	−0.120 *	−0.084	0.690 **	1			
GI—Group Influence	3.696	0.887	−0.115	−0.135 *	−0.093	−0.094	0.679 **	0.584 **	1		
CI—Customer Intention	5.606	0.890	0.675 **	0.662 **	0.645 **	0.617 **	−0.127 *	−0.130 *	−0.140 *	1	
CB—Customer Behavior	5.656	0.937	0.629 **	0.608 **	0.575 **	0.579 **	−0.280 **	−0.201 **	−0.214 **	0.754 **	1

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4. Varimax-rotated component analysis factor matrix.

Component	Factor Loading	
	1 (Positive Factor)	**2 (Negative Factor)**
IS—Information Search	0.934	
RS—Recommendation System	0.941	
PD—Dynamic Pricing	0.919	
CS—Customer Services	0.920	
PS—Privacy and Security		0.900
SA—Shopping Addiction		0.862
GI—Group Influence		0.857

Notes: Factor loading less than 0.40 have not been printed; extraction method: principal component analysis.

4. Results

We have used a two-stage analytical procedure to present results. First, a confirmatory factor analysis was done to assess the measurement model. Second, the structural model and regression analysis were examined.

4.1. Measurement Model

The factor loading should be greater than 0.70 [39,49]. For this study, all standardized factor loadings were significant, ranging from 0.759 to 0.993. The construct reliability was tested using composite reliability measures that assess the extent to which factors in the construct measure the latent concept. Convergent validity of the CFA results should be supported by composite reliability (CR) and average variance extracted (AVE). Hair [39] and Maichum, et al. [49] stated that the estimates of CR and AVE should be higher than 0.700 and 0.500, respectively. As presented result in Table 5, the CR and AVE value ranged from 0.851 to 0.927 and 0.657 to 0.762, respectively, passing their recommended levels. Discriminant validity is established using the latent variable correlation matrix, which has the square root of AVE for the measures on the diagonal, and correlations among the measures as the off-diagonal elements (Table 6). Discriminant validity is determined by looking down the columns and across the rows and is deemed satisfactory if the diagonal elements are larger than off-diagonal elements [51].

Table 5. Standardized factor loadings, Composite Reliability and Average Variance Extracted of the measurement model.

Construct	Item	Standardized Factor Loading	Composite Reliability (CR)	Average Variance Extracted (AVE)
Positive Factors (PF)	IS	0.789 ***	0.927	0.762
	RS	0.933 [a]		
	PD	0.883 ***		
	CS	0.881 ***		
Negative Factors (NF)	PS	0.895 ***	0.851	0.657
	SA	0.771 [a]		
	GI	0.759 ***		
Customer Responses (CR)	CATI	0.888 [a]	0.857	0.749
	CDAC	0.843 ***		

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. [a] Values were not calculated because loading was set to 1.000 to fix construct variance.

Table 6. The latent variable correlation matrix: Discriminant validity.

	Positive Factors (PF)	Negative Factors (NF)	Customer Responses (CR)
Positive Factors (PF)	0.87		
Negative Factors (NF)	−0.16	0.81	
Customer Responses (CR)	0.80	−0.24	0.86

Note: Square root of AVE is on the diagonal.

Table 7 shows the CFA results for measurement model fit indicators. The recommended acceptance of a model fit requires that the obtained goodness of fit index (GFI), the adjusted goodness of fit index (AGFI), and the normed fit index (NFI) should be greater than 0.900; the comparative fit index (CFI) should be greater than 0.950; and the root mean square error of approximation (RMSEA) should be less than 0.080 [49,52]. The ratio of the chi-square value to degree of freedom is 1.571, which is below the recommended value of 5.000. Furthermore, the other fit index values for GFI, AGFI, NFI, CFI and RMSEA were 0.970, 0.947, 0.979, 0.992 and 0.046, respectively, which are suitable considering the recommended values. Thus, the measurement model had a good fit.

Table 7. Measurement model fit indicates.

Fit indicates	Criteria	Indicators	Sources
Chi-square/df (degree of freedom)	<5.000	1.571	[53,54]
Goodness of Fit Index (GFI)	>0.900	0.970	
Adjusted Goodness of Fit Index (AGFI)	>0.900	0.947	
Normed Fit Index (NFI)	>0.900	0.979	
Comparative Fit Index (CFI)	>0.950	0.992	
Root Mean Square Error of Approximation (RMSEA)	<0.080	0.046	

4.2. Structural Equation Model

The results of the structural model and the standardized path coefficient indicated effect among the constructs of the model was shown in Figure 2. The positive relationship between positive factors and customer responses (H_1: $\beta 1 = 0.789$, $t = 14.852$, $p < 0.001$) pointed out that H_1 was supported. Regarding H_2, the negative estimate of coefficients between negative factor and customer responses has significant negative effects (H_2: $\beta 2 = -0.124$, $t = 2.542$, $p < 0.05$). However, the comparison between the path coefficient of positive factors and negative factors ($\beta_{PF} = 0.789$, $\beta_{NF} = 0.124$), respectively) clarifies the different roles that positive factor and negative factor in customer responses. The comparison clearly demonstrates the critical role of positive factor of applying Big Data analytics in customer responses.

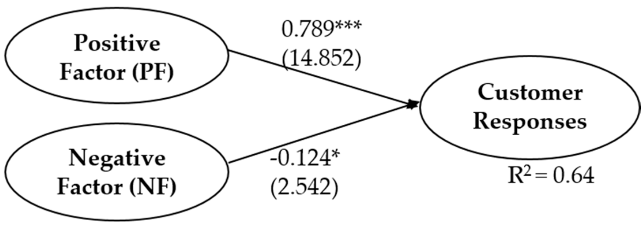

Figure 2. The results of the research model. (Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; value within the parenthesis is t-value.)

Table 8 and Figure 3 present the results of regression analysis. Regression analysis indicates that all positive and negative factors can explain 49.3% variance of Intention. Customer intention is positively significantly influenced by information search, recommendation system, dynamic pricing and customer services. Conversely, customer intention is negatively significantly influenced by privacy and security, shopping addiction and group influences. All factors of applying Big Data analytics would influence customer's intention.

The results also indicated that all the positive and negative factors can explain 47.4% variance of customer behavior. Behavior is positively significantly influenced by information search, recommendation system and dynamic pricing. Moreover, customer behavior is negative significant influenced by privacy and security, shopping addiction and group influences. Compared to all factors of applying Big Data analytics, information search is the most significant influential factor that would improve customer behavior on buying products of e-vendor. However, customer service factor is no more an important effect to customer behavior.

In different stages of the consumer responses hierarchical model, the effects of Big Data application on consumers are different. In the stage of customer intention to its applications, customers pay more attention and more interest of positive applications than negative applications. In the stage of customer behavior, most positive factors and negative factors of application had significant impact on customer responses, except customer services. In this case, customers care more about other application factors than customer service.

Table 8. Results of regression.

		Intention	Behavior
Positive Factor	Information Search (IS)	0.244 ***	0.384 ***
	Recommendation System (RS)	0.259 ***	0.153 ***
	Dynamic Pricing (PD)	0.201 ***	0.066 **
	Customer Services (CS)	0.182 ***	0.172
Negative Factor	Privacy and Security (PS)	−0.030 ***	−0.073 **
	Shopping Addiction (SA)	−0.016 ***	−0.101 *
	Group Influences (GI)	−0.021 ***	−0.100 *
	R^2	0.493	0.474

Notes: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001.

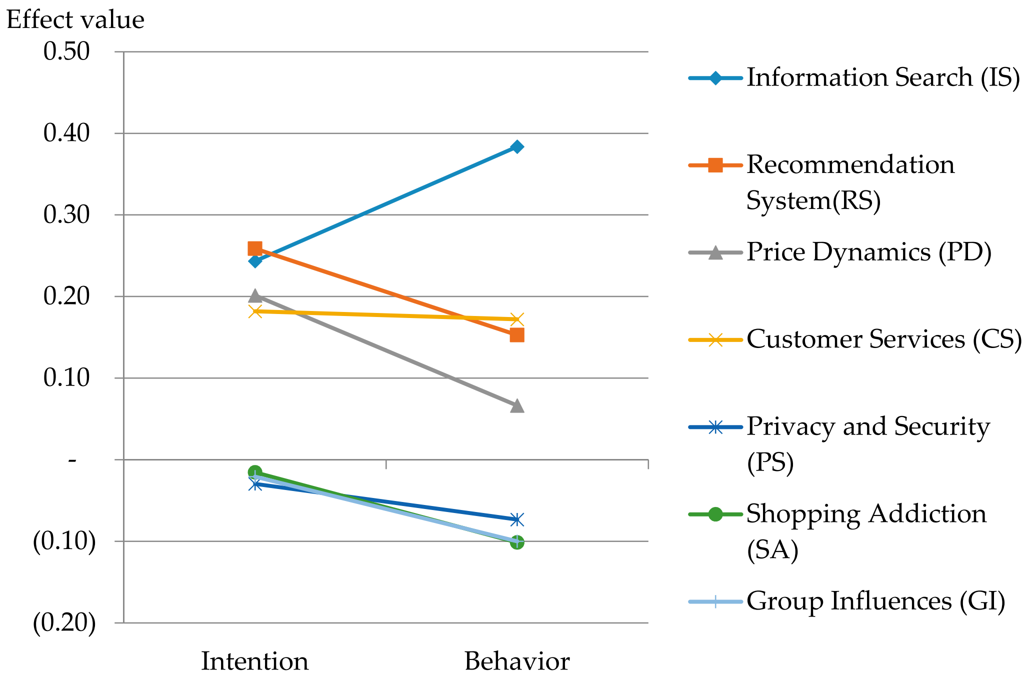

Figure 3. Results of regression.

Positive factors of applying Big Data analytics have positive influence on customer responses. Among four positive factors, we can see that the information search is the most important factor. All negative factors of applying Big Data analytics have negative influence on customer responses.

5. Discussion and Conclusions

The aim of this study is to explore the factors of applying Big Data analytics and how it effects to customers' responses in the B2C e-commerce environments using application of Big Data analytics. The first result showed that information search, recommendation system, dynamic pricing and customer services were found to have significant positive effects on customers' responses. Privacy and security, shopping addiction and group influences were found to have significant negative effects on customers' responses. Tang and Wu [48] stated that decision making influences the recommendation system, information search, reputation system, and virtual experience on online consumers in the Big Data environment. Data privacy and data security is an unavoidable problem in Big Data era [55].

The paper attempts to address several implications that may help in developing marketing strategies for e-commerce under Big Data era. Recommendation system allows consumers to locate and match their preferences and interest easily, thereby increasing the customers' intention and behavior. Moreover, from customer's perspective, customers want to receive from recommendation system to improve their decision making in buying, so the products meet their own preferences with more satisfaction. Furthermore, products are recommended by a system are more reliable, which leads to gaining more customers' confidence, and feeling pleasure and motivation. With the development of information technology and e-commerce, the problem of information overloading and complexity of choice shall be more and more regular. Therefore, e-vendors should improve the matching result information search for reducing their cognitive costs. Dynamic pricing and improved customer service are applications that should be noticed to make customers more satisfied.

Positive and negative effects simultaneously coexist, thus affecting customer responses. This is consistent with two distinct constructs being able to coexist at the same time [56–58]. The results showed that positive and negative factors activate different effects to customers' responses, implying that they are distinct constructs which are associated with different neurological process. Especially, the positive factor is connected with brain liked to anticipating rewards, positive emotion. Negative factor is related with brain liked to intense negative emotions, fear, and loss. The result also illustrated that the role of positive factor was clearly influenced on customers' responses than negative factor. This finding highlights notification that consumers using website applied Big Data analytics paying more attention with positive factor. Therefore, e-vendors should try to apply Big Data analytics to attract customers' intention toward their applications. This could help in influencing the customers to do online purchase.

Positive and negative factors had different impacts on customer' intention and customer's behavior. In positive part, information search, recommendation system, dynamic pricing and customer services has high significant effect on the intention with recommendation system having a strongest influence followed by information search, dynamic pricing and lastly customer service. With recommendation system exerting a strong impact, e-vendors should apply this Big Data analytics application to catch customers' intention. Information search had highest influence to customer behavior, followed by recommendation system and dynamic pricing. Customer service had no significant effect to behavior. As demonstrated in Figure 3, these findings indicated that recommendation system firstly catches highest customers' intention but it has reduced customers' behavior. This can be explained that recommendation system is an application which gives to customers with passive condition. Information search had significant influence customers' intention and after that improved customer behavior. A customer in active condition might want to search information. The information provided by Big Data analytics application satisfied customers. In negative part, privacy and security, shopping addiction and group influence had significant negative effect on customers' intention and behavior. Privacy and security problem has the strongest influence to customers' intention but the lowest impact to customers' behavior. It can be explained because e-commerce firms are able to identify security and fraud detection under Big Data analytics [8]. Therefore, privacy and security is not the biggest customer concern about negative of applying Big Data analytics. The result implied as the change of slope of effect value, the shopping addiction had big slope change than group influences, privacy and security. It raises a question for e-vendors that customers had to realize biggest issue about shopping addiction because of the benefit of applying Big Data analytics. Therefore, customers should understand and control themselves away shopping addiction.

Applying Big Data analytics has emerged as the new innovation and new method of the e-commerce landscape. Applying Big Data analytics increasingly provide positive value to customers by using dynamic, processes, and technologies to analyze data to customize consumers' need. Leading e-commerce applying Big Data analytics such as Google, eBay, Amazon, Taobao, and others have already applied and gained much business value. However, applying Big Data analytics also brings some negative issues to customers' responses. This study presents several positive factors and negative factors and their effects to customer responses for application of Big Data analytics. Regarding Big Data era, studies reflect that, after 2017, data analysis technique will be a competitive necessity. Therefore, companies need to start to adapt to the trend using Big Data analytics in order to survive in the dynamic and digitalized markets. This is a process that deals with data, sources, skills, and systems to create competitive advantages. The concept of big data has been developed, and should be applied now to improve strategies, prediction and decision making for better customer relations. However, applying Big Data analytics can also have pros and cons. E-vendors can optimize the advantages of applying BDA but do not inclined to over reliance on BDA in order to avoid negative aspects. Validating checks with their real case would make suitable and effective marketing strategies.

In addition, e-vendors that would like to work with Big Data analytics would require having enough data. This procreates, as a form of rule with the online citizen behavior. Not only customers contribute their information but also e-vendors also add data to build big data.

6. Limitations and Future Research

The limitation and future research of this study are mainly in three points. First, the sample of this study is limited in potential customers, so future studies may include samples from a diverse demographic population. We further recognized that sample respondents were Vietnamese and would be a limitation to the study. However, the contribution of this study is worthy and applicable for developing countries such as Vietnam. Further studies may take a cross-culture comparison between different countries. Secondly, the present study used user's views of their response as a dependent variable. Even though users' view is frequently used as a surrogate measure of behavior, it does not accurately predict actual buying situation. Thus, the results found in the present study should be understood and practiced with caution. Similar future studies should measure to fit in actual online shopping behavior such as information search, real recorded ordering, and purchase amount as a dependent variable. Thirdly, the longitudinal method is recommended for future research in order to explore other impacts of applying Big Data analytics and capture the change of customers' responses.

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