UNDERSTANDING BIG DATA EFFECTS ON BUYING INTENTION THROUGH USEFULNESS, RISK AND TRUST PERCEPTIONS OF CONSUMERS TOWARDS WEBSITES

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BY

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ABSTRACT

The 21st century is a period when technology and data flow are very fast. Many innovative fields such as big data, networking and cloud computing have emerged in this field. Marketing 3.0, 4.0, business analytics and the use of big data are the latest technology and technologies that are related to marketing. In this study, among the developing and increasing new data flows, this is called big data, it is aimed to investigate the effect of customer buying intention on the online marketing system. The study aims to understand the relationship between trust, website usefulness and risk perception of consumers and online purchase intention. Besides, variables developed according to purchase intention and whether there are purchasing intention effects were discussed with a model. A research had been conducted with a sample size of 336. Hence, findings related to these variables are presented.

As a result of the study, variables that affect the customer buying intention (customer service, group effects, dynamic pricing, recommendation system, perceived benefit, trust, perceived risk) were tested with a model. 17 hypotheses were established and only 5 hypotheses could not be supported. It is concluded that Trust, perceived usefulness influences customer buying intention in online shoppers. It has been observed that perceived risk does not affect customer buying intention. Also, according to demographic data, we can say that as the percentage of online shopping increases, customer buying increases in direct proportion to intention, trust, and perceived usefulness and that it is inversely proportional to perceived risk. Besides, it has been observed that the purchasing tendency of the 35-44 age group is more effective through online websites than other age groups. In this age of online shopping, the results of this study are critically important to understand the weight of

concepts like trust and risk on consumer choices. Moreover, it is aimed to shed a light on future studies.

Keywords: customer buying intention, big data, big data infrastructure, data monitoring, online marketing, trust, usability, risk, websites

ÖZET

21. yüzyıl, teknoloji ve veri akışının çok hızlı olduğu bir dönemdir. Bu alanda büyük veri, ağ, bulut bilişim gibi birçok yenilikçi alan ortaya çıktı. Marketing 3.0, 4.0, iş analitiği ve büyük veri kullanımı günümüze kadar gelen son teknoloji ve pazarlama ile ilişkisi olan teknolojilerdir. Bu çalışmada gelişen ve artan yeni veri akışları arasında buna büyük veri adı verilir, müşteri satın alma niyetinin çevrimiçi pazarlama sistemindeki etkisinin araştırılması amaçlanmıştır. Çalışmanın temel amacı, güven, web sitesi kullanışlılığı ve tüketicilerin risk algısı ile çevrimiçi satın alma niyeti arasındaki ilişkiyi anlamaktır. Ayrıca satın alma niyetine göre geliştirilen değişkenler ve satın alma niyet etkilerinin olup olmadığı bir model ile tartışılmıştır. Bu değişkenleri anlamak için 336 kişiden oluşan örneklem üzerinde analizler yapılmıştır. Çalışma sonucunda müşteri satın alma niyetini etkileyen değişkenler (müşteri hizmetleri, grup etkileri, dinamik fiyatlandırma, öneri sistemi, algılanan fayda, güven, algılanan risk) bir model ile test edilmiştir. 17 hipotez kurulmuş ve sadece 5 hipotez desteklenememiştir. Güven ve algılanan kullanışlılığın online alışveriş yapan müşterilerin satın alma niyetine etkisinin olduğu sonucuna varılmıştır. Algılanan riskin, müşteri satınalma niyetine etkisinin olmadığı gözlenmiştir. Ayrıca demografik verilere göre online alışveriş yapma yüzdesi arttıkça müşteri satin alma niyeti, güven ve algılanan kullanışlılık için doğru orantılı arttığını, algılanan risk için negative ilişkide olduğunu söyleyebiliriz. Ayrıca 35-44 yaş grubunun diğer yaş gruplarına göre, satın alma niyetinin online web siteleri üzerinden daha etkili olduğu görülmüştür. Bu çevrimiçi alışveriş çağında, bu çalışmanın sonuçları, güven ve risk gibi kavramların tüketici tercihleri üzerindeki ağırlığını anlamak açısından kritik derecede önemlidir. Ayrıca ileride yapılacak çalışmalara ışık tutması hedeflenmektedir.

Anahtar Kelimeler: müşteri satın alma isteği, büyük veri, büyük veri altyapısı, veri izleme, online marketing, güven, kullanışlılık, risk, web siteleri

To mum and dad, sister, and brother

especially for their kindness, devotion, and

endless support.

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1. INTRODUCTION

1.1. The Importance of the Study

The exponential growth of technology has brought a new data-based industry. Simply put, this type of industry collects, aggregates, and commercializes personal data and information. The digital activities of millions of people around the world can be tracked with a variety of new techniques, from a store's loyalty/credit cards to targeted advertisements found on social media platforms like Facebook, Twitter, Instagram, and more. Personal data, including both online and offline behaviour, is aggregated, analyzed, and then sold to different types of companies and companies (Marwick & Boyd, 2014). Companies that collect, combine, and analyze this type of data are known as data brokers. Data brokers represent this wave of change that deals with personal information and how it is processed both online and offline. This dramatic change has created a new movement towards what is known as "Big Data." For example, Big Data consists of only raw "small data". In many cases, this small data gives deep personal information about a consumer's individual and purchasing profile and consumer's habits. Doug Laney, a technology analyst, first described Big Data as "high-volume, fast and diverse information assets that require cost-effective, innovative forms of information processing for advanced insight and decision making." (S. Sicular, 2013). Businesses in every industry value such insights that were once absent before this growth in technology and are concerned with how these analytics can be collected and used. This evolution of service intelligence combines both online and offline user behaviour to determine what consumers are busy with, what they want to spend money on, what kind of service they prefer, and how and why they keep them coming back. Companies use Big Data not only to target their communities and consumers but also to give the consumer exactly what they want and customize the consumer experience to suit their interests (Byfield, 2014).

Privatization allows industries to find new ways to increase consumer loyalty, and with the help of Big Data, companies can easily match consumer-related products/brands with targeted consumer profiles and data-driven decisions. Rather than relying solely on guesswork or sentiment, the facts and figures are now available (Lavalle et al., 2011).

Big Data attracts attention worldwide with various Big Data definitions. Big Data is a dataset that can be captured, transmitted, collected, stored and analyzed (Manyika et al., 2011). Another definition is that Big Data is generated from an increasing number of sources, including web sites consumers, mobile transactions, user-generated comments and contents and social media, as well as content deliberately generated through sensor networks or business transactions such as customer information and purchases (George et al., 2014).

The research aims to understand big data in online marketing and highlight relationships among perceived usefulness, perceived risk, trust, and customer buying intention in Turkey. These relationships are viewed as a significant issue in the field of customer buying intention since the heat of research on big data by enterprises and academia is increasing year by year.

1.2. Objective of The Study

This research is to understand the relationship of big data with online marketing and to understand the variables consisting of big data and customer buying intention. Hence, perceived benefit, trust, perceived risk, customer service, group influences, recommendation systems, dynamic pricing, online websites that can affect the purchasing intention of customers while shopping online are handled with variables.

Also working with these variables to achieve a significant relationship between descriptive findings that may affect the intention of buying customers in Turkey has been requested. In previous similar studies, the effects of the customer buying intention variables of websites with big data infrastructure and the effects of negative and positive big data mainstream application on the behaviour of the website customers were examined (Lee et al., 2013; Min & Zhong, 2015). On behalf of big data research with impact in Turkey and customers to understand the intention of buying through online websites are expected to fill an important gap.

In the research, the model and the model with dependent (customer buying intention) and independent variables (trust, perceived usefulness, perceived risk, customer services, recommendation system, group influences, dynamic pricing) to understand the benefits of consumers for websites, risk and trust perception and the effects of big data are tested.

1.3. Scope of The Study

In the first chapter of the study, the introduction part presents the objective and importance of the study.

The second part presents a literature review on the concepts of marketing and big data. In this part, online marketing and big data definitions are described, as well as implications of big data in the marketing field.

Based on the literature section, the relevant variables are defined and explained in this section. Then, the hypotheses are defined according to the variables and the research model is determined.

In the fourth section, information about the research design and data collection within the research method is given. In the finding section, the information about descriptive findings, reliability, normality, and hypothesis tests are made according to questionnaire data. The result of the hypotheses according to the correlation and regression results are given in this section.

Section six summarizes the study by including the results of the findings. In the last section, limitations of the study and suggestions for further studies are given.

2. LITERATURE REVIEW

2.1. The Era of Marketing 3.0: The concepts behind the Era

Before entering Era 3.0, it is important to understand the two driving forces determining the rise of modern marketing (2.0): the beginning of the 90s and the need to create demand. Consumers can now access the network and thus become connected and therefore well-informed people. As a result, companies started to develop brand management and differentiation strategies to add value to the brand and invest heavily in experimental and emotional marketing (Erragcha & Romdhane, 2014). Formerly as a focus on mass production (1.0), the focus has become the consumer as someone who has specific needs and needs to see the value of a brand to take care of it. Marketing 3.0 appears exactly in this scenario but is driven by 3 changes: collaboration, cultural marketing, and self-realization (Varey & Mckie, 2010). Establishing the mission in Marketing 3.0 is about providing customers with business intentions that can make their lives better. There is often a great story behind the emergence of a good mission, and this story is often exciting and engaging and brought to the attention of its customers, users and employees.

The brand's mission does not need to be sophisticated or complex, it should be simple to provide good flexibility in assigning focus to be followed, demonstrating that the organization's mission belongs to the customer and that the company is responsible for fulfilling its mission. According to Kotler, Kartajaya consumer empowerment is due to the increase in information shared via social networks (Kotler, P., Kartajaya, H., & Setiawan, 2010). Consumers do not see that the traditional media does not meet their wishes, they now go to forums, meaningful or collaborative social networks to learn and discuss the product of interest, verify the quality and accuracy with the analysis of other consumers who buy the product. product and then consume it.

Therefore, consumer empowerment is the basis for a good definition of the brand's mission in marketing 3.0 (Kotler et al., 2007).

Kotler, Kartajaya and Setiawan (2010), the vision in marketing 3.0, the manager has to be aware that the return of the activities developed in the company not only go to the organization but all employees. your interested parties. Like consumers, employees, channel partners, government, nonprofits and the general public. Because a successful organization does not achieve success on its own, and the main vision in marketing 3.0 is that the benefits must address everyone interested in the organization. The author also states that the corporate vision must involve the concept of sustainability, as this will be essential for long-term competitive advantage(Kotler, P., Kartajaya, H., & Setiawan, 2010). While the mission has its roots in the past, when the company was founded, the vision has to do with the invention of the future or what we want it to be. The definition of values in marketing 3.0 according to Kotler, Kartajaya and Setiawan (2019) is a set of corporate priorities that articulate behaviours that benefit communities inside and outside the organization. These communities encompass the organization's customers and employees (Kotler et al., 2019). To reach the mind, heart and spirit of its stakeholders, the organization must also provide economic viability, environmental awareness and social responsibility among its employees.

2.2. Marketing 4.0

According to Kotler (2017), Marketing 4.0 is a collective effort to take the customer from another dimension, for this, it is necessary to cover all aspects and to create a deeper communication (Kotler et al., 2017). The result is trade growth. Marketing 4.0 uses artificial intelligence to increase the productivity of strategies and leverages people's commitment to strengthen the company's customer bonds. In the current digital economy, consumers have become more demanding and want to buy products and services almost instantly, so strategies focus on satisfying the public by meeting all their expectations.

Tullman (2017) states that a way should be found between the customer and the company, considering the rapid technological changes in the environment and thinking that they are accelerating (Kotler, 2017). Marketing 4.0 suggests understanding and adapting to a new digital world. Digital media, including social media or social networks, can become one of the most important points for reaching the consumer's mind and indirectly persuading him to buy a product or service.

Kumar (2017) explains that the recent digital transformation we are in needs to be analyzed more and more and that we, as marketers, need to overcome this by creating new strategies (Kotler, 2017). Marketing is no longer just a traditional strategy for reaching the end consumer first, but also about building good relationships with segmented communities with different needs and high expectations. A brand needs to be dynamic enough to act and exceed expectations in all situations, so loyal brand advocates who are loyal consumers and willing to defend their favourite brands are ahead of different impulsive netizens. In this way, companies earn more.

Day (2017) thinks that Marketing 4.0 has these challenges thanks to the digital transformations we are a part of, that in more complex scenarios in the future, vendors should learn to interact with new digital changes using digital connectivity. As technology has improved so much, we can find new connectivity tools as a great ally to deliver a product or service, also strengthen traditional marketing tools and in this way affect customer buying intention (Kotler, 2017).

While Vieira (2017) states that the variety and speed of digital transformations contribute greatly to doing business, marketing 4.0 creates a different company profile for consumers by evaluating the construction of a new strategy to face the current technological revolution (Kotler, 2017). Today's customers, in addition to feeling part of the organization, want to receive good service with excellent product quality and minimum time; This idea is supported by the same company that is always looking for the opinion of the public to perfect a final product.

After examining the contributions of the main authors, thinks that the definition of Marketing 4.0 is a different way of doing business through adapted new digital trends, ranging from applications, websites, social networks and others, these tools help to have more of the interconnected world, that way the customer and the company has a more direct communication. As Traditional Marketing is the beginning of the relationship between the company and the customer, creates awareness and interest, and as the interaction develops and the customer demands a closer relationship, Digital Marketing's Marketing becomes important and increases the promotion of the company to the customer in a more personalized way.

2.2.1. Dimensions of marketing 4.0

Kotler (2017), when marketing 4.0 is evaluated in two dimensions, which has undergone a significant technological evolution, the merger that can be mentioned in online and offline channels is known as omnichannel. These changes in recent years have helped the market to become increasingly inclusive, where social media helps eliminate geographic and demographic barriers, allowing people to connect and communicate and thus companies innovate through communication.

The world is connected and a great key challenge for brands and companies is to integrate online and offline elements in the total customer experience at the time of purchase; the customer purchasing process is becoming more social than it has previously been, customers are becoming more distrustful of brand communications and are relying instead, on the F factor (friends, families, fans and followers). Marketers in today's digital economy must focus on three main sources of influence: their own, others' and external (Kotler, 2017).

The main objective of Marketing 4.0 is to gain customer support, combining online interaction and digital marketing, and offline and traditional marketing; the combination of both symbolizes immediacy and trust, the omnichannel strategy is strongly supported by machine-to-machine artificial intelligence (mobile phones, PCs among others), which makes Marketing much more efficient. Online and offline interaction must coexist and work together to provide a different and superior experience to consumers, it is about creating a nexus with the customer to fill them with information, create communication and finally make them their brand advocate (Kotler et al., 2017).

Today's most successful brands must show themselves to be more friendly to the public since consumers are bombarded with unnecessary advertising, which makes people feel less and less interested in acquiring a product from a certain brand or company; That is why if a company listens socially to its public, it can know what it thinks of the company, if it is willing to buy something or if it would recommend it to someone close to it.

2.2.2. Online channel marketing

It is one made up of a group of techniques supported by digital media whose objective is to take advantage of every opportunity within its reach and thus promote a company or brand more effectively. The online channel offers a range of opportunities for companies that make use of this tool. In the digital context, new networks emerge every day and it is through this channel that the customer can express themselves freely about the product they want.

According to Kotler (2017), the behaviour of consumers is influenced by connectivity nowadays, they seek the simplest and most accessible for them since most are eager and enthusiastic to make the purchase (Kotler et al., 2017).

Creating a strategy for the online channel is very different because the customer is the one who decides what content they want to see and what product they want to consume when they want to have it and how they want to get it. Why is it more boring for companies to interrupt customers and try to grab their attention, content on the internet must be engaging and relevant, and interactive so that it can grab the customer's attention on a platform, often this strategy is supported by social media, informative content and search engines. After all, this is a more effective and cheaper strategy to reach the customer than a television commercial.

Connectivity accelerates market dynamics, enabling companies to collaborate with the public, this is the only way for a brand to succeed in the digital economy; it is the link that transforms customer behaviour, so it should have a holistic approach to the link. First, there is mobile connectivity that is more accessible to the public, these are facilitated using screens, smartphones, laptops; A user can see a television ad, but will always look for information about it on their mobile phone. On the other hand, there is experimental connectivity where the brand deals with the customer experience that does everything possible to make itself superior, at this point, it is the level of connectivity depth that matters most. Finally, there is the social connection where the connection between the company and the customer takes priority.

Online Marketing channels are classified as follows:

• SEM (Search Engine Marketing): These are all those actions aimed at publicizing a website through search engines such as Google, Yahoo, Bing, among others; These actions are mostly paid ad campaigns on those engines. Your ultimate goal is visibility to other pages and targets a qualified audience quickly.

Thanks to this method, it can also appear on other websites that are related to the company.

• SEO (Search Engine Optimization): It is the optimization of advertising in search engines and thus improve the visibility of a company's website. In this context, we have 2 important factors: Authority, which is the popularity of a website and relevance, which is the relationship that a page has to a specific search.

• Rich Media: They are different from traditional graphic advertisements, they allow the user to interact with videos, sounds, animation; thus they manage to increase the effectiveness of their ads. An added benefit of these is that they can scroll and expand when a user reaches a section of the web.

• E-Mail Marketing: It is defined as the massive sending of emails to certain groups of contacts. It is the most effective online marketing tool. Its objective is to promote a message or advertising by sending emails.

• Affiliates: Also called Influencers are the people who are willing to promote the company from their websites, social networks or blogs, and in this way greater traffic is achieved for the company's website.

• Directories: These are the links that the company's website can have with other directories on the Internet. You can have a greater presence and generate more traffic if you have specialized directories.

• SMM (Social Media Marketing): These are all the actions carried out to bring traffic to a website with the help of social media, a new communication link to related companies and products with each Internet user. It aims to expose a business through viral videos, blogs, apps, and more.

Within this method, we find the most popular social networks such as Facebook, Instagram, Twitter, Youtube, WhatsApp, LinkedIn, Pinterest and Yelp; being the most used and effective Facebook followed by a growing Instagram.

• SMO (Social Media Optimization): It is the optimization of results through social media strategies to achieve the proposed Marketing objectives.

Digital Marketing strategies generate more value for the company, this is possible by creating content that can consumers' doubts, as well as offering them a solution to the possible problem they may have.

According to Aurora (2015), access to platforms and social networks has meant a major evolution since the invention of the first, all with the main goal of building intimate relationships and gaining mutual benefit based on similar interests, These same interests are managing new connections and new business networks.

2.3. Business Intelligence, Market Intelligence and Marketing Intelligence

Business Intelligence is the system that supports management decision making in the broadest sense of the word, encompassing the processes of data collection, exploration, analysis and interpretation and leading to the rationalization of the decision-making process to create economic value for a company (Surma, 2011). About its objective, business intelligence is used to understand the resources available in the company; future trends and directions in the markets, technologies and the regulatory environment in which the company competes; and the actions of competitors and their implications in the competitive environment (Negash, 2004). Another aspect argues that the business intelligence process is based mainly on internal company records, such as sales, distribution and purchases, and the collection of data from the external environment of the company would be an activity attributed to market intelligence. The objective of incorporating market information in the business intelligence process is, therefore, to provide decision-makers with a “more complete image" of corporate performance in certain market conditions.

Market intelligence is a comprehensive term that includes applications, infrastructure, tools and best practices that allow access and analysis of data to improve and optimize decision making and business performance (Sallam et al., 2014). In this case, market intelligence would be a broader concept than business intelligence, showing that there is misalignment regarding these concepts for different authors. The objective of market intelligence is to allow the easy interpretation of large volumes of data to identify new opportunities to implement effective strategies, providing companies with a competitive advantage and long-term stability in the market (Lees-Marshment et al., 2009). In this sense, Market intelligence can be obtained through formal (for example, reports) and informal (for example, conversation in the salon) mechanisms from various personal and public sources (Maltz & Kohli, 1996).

2.4. Business Analytics, Marketing Analytics and Consumer Analytics

The concept of Business Analytics, according to Davenport and Harris, deals with extensive use of data, statistical and quantitative analysis, explanatory and predictive models and fact-based management to drive decisions and actions. Analyzes can be inputs for human decisions or they can drive fully automated decisions (Davenport et al., 2007).

Evans and Lindner (2012) argue that Business Analytics would be a convergence of three fundamental disciplines: statistics; business intelligence (BI) and information systems (IT); and modelling and optimization (traditionally, operational research). Also, they argue that Business Analytics is commonly seen from three perspectives: descriptive, predictive and prescriptive (Evans & Lindner, 2012). The descriptive analysis summarizes data in graphs and reports and is the most used and best understood type of analysis that serves to understand past and current business performance, as well as for decision making. Predictive analysis, on the other hand, analyzes past performance to predict the future, examining historical data, detecting patterns or relationships between them, and then extrapolating those relationships forward in time in the form of projections. Finally, the prescriptive analysis uses optimization to identify the best alternatives to minimize or maximize some objective, being widely used in several business areas, including operations, marketing and finance.

Chen, Chiang and Storey (2012) use Business intelligence& Analytics (BI&A) as a unified term and treat Big Data Analytics as a related field that offers new directions for Business intelligence& Analytics (BI&A) research (Chen et al., 2012). More recently Seddon, Constantinidis, Tamm and Dod (2017) defined Business Analytics (BA) as “the use of data for more solid and evidence-based business decision making and through Business intelligence (BI)”, the latter being a set of tools based on Information Technology (IT), such as data warehouses, online analytical processing (OLAP), statistical and quantitative tools, visualization tools and data mining tools (Seddon et al., 2017).

Davenport and Harris (2007) treat Analytics from a broader perspective of the firm and for any type of company. The concept of marketing analytics, on the other hand, brings an internal view of the business, emphasizing the issue of accountability of marketing or marketing accountability, that is, the analysis of the results of marketing actions and your return to the company (Davenport et al., 2007). Following this line, they define Marketing Analytics as processes that involve the collection, management and analysis of data - descriptive, predictive and prescriptive - to obtain information on marketing performance, to maximize the effectiveness of marketing control instruments and to optimize corporate return on investment. Along the same lines, Rackley (2015) treats marketing analytics as a process of identifying valid metrics as indicators of marketing performance in the pursuit of your goals, tracking these metrics over time and using the results to improve the marketing operation (Rackley, 2015).

Considering the most elementary level of Marketing Analytics, namely, consumer/client, the concept of Consumer Analytics was arrived at, defined as the extensive use of data and management models based on facts to drive decisions and actions, where data and models are defined at the individual customer level (Bijmolt et al., 2010). Erevelles, Fukawa and Swayne (2016), in turn, inserted the concept of Consumer Analytics in the context of Big Data . Thus, the concept of big data consumer analytics was defined, as the extraction of hidden information about consumer behaviour from big data and the exploration of the insights generated through interpretations that generate some kind of advantage for the company. (Erevelles et al., 2016)

2.5. Big Data

The beginning of the digital age in the year 2000 and the significant increase in the capacity for creating and storing data on the internet were the main drivers of the creation of the term big data (Hilbert & López, 2011). The main proposal of big data is to promote the inclusion of information from the web in the context of data analysis of the institutions. In this way, managers start to define business strategies using data that evolves in real-time in the digital environment. With the analysis of these large volumes of data, organizations start to make more assertive decisions while remaining competitive in the global world.

Segaran (2013) narrates that big data is a broad term for very large or complex data sets that traditional data processing applications are insufficient (Segaran, 2013).

Challenges include analysis, capture, data curation, research, sharing, storage, transfer, viewing, consultation and private information. Big data, therefore, is a term used to designate the growth of information, large in volume, diversified in format and received at high speed. In the marketing environment, information systems aim to provide relevant, reliable and available information in a short time, so that decisions are made and can generate value for organizations (Salvador & Ikeda, 2014).

The term big data first appeared in the 2001 report by the META Group (Gartner company), authored by analyst Douglas Laney. According to, the definition of big data is related to the challenges of data growth and opportunities, such as being three-dimensional, that is, the increase in volume (amount of data), speed and varieties (Laney, 2001). In the view of Laney (2012), the Big Data context usually includes data sets with sizes beyond the capacity of software tools, commonly used to capture, treat, manage and process data within a tolerable elapsed time. Big data requires a set of techniques and technologies with new forms of integration to reveal insights from data sets that are diverse, complex and large-scale (Beyer & Laney, 2012).

According to McAfee and Brynjolfsson (2012), the main difference between Big data and conventional CRM or ERP systems is the ability to analyze and store data. Big data solutions expand the data analysis capacity, as they have a high storage capacity, allowing a quick analysis of this data, which can generate useful information for the business, almost in real-time (McAfee et al., 2012).

As discussed, the concepts for the term are numerous and several others are identified in the literature. According to Franks (2012), there is no consensus on the concept of big data, despite that, many concepts share the essence of the term and the main points are addressed by many authors as the dimensions of the phenomenon (volume, velocity, variety, value and veracity) (Franks, 2012).

The five characteristics that define Big Data are volume, velocity, variety, veracity and value. Together, these characteristics create needs for new skills and new knowledge, to improve the ability to deal with information, considering the veracity and the need to add value to the organizations' business (Taurion, 2013).

According to, the first characteristic deals with volume, because of the immense amount of data being processed and increasing at each moment. Then, the characteristic of the variety, since the concept of Big Data encompasses the treatment of structured data and mainly unstructured data, which represent about 90% of the total volume and come from different types and sources. The third characteristic refers to the speed, for the speed with which the data is generated and in the same way they must be processed and analyzed. In the context of veracity, the data collected and mined must contain authenticity and represent reality. Finally, the value characteristic, which emphasizes the relevance of the need for predictability of return on investment in Big Data analysis (Taurion, 2013).

For Segaran (2013), the analysis of data sets can find new correlations of local business trends, prevent disease, fight crime and so on. Data sets are growing rapidly, in part because they are increasingly coming together through cheap and numerous devices for detecting mobile, aerial (remote sensing) information, software logs, cameras, microphones, radio frequency identification, readers and wireless sensor networks (Segaran, 2013). The world's per capita technological capacity to store information has practically doubled every 40 months since the 1980s, and as of 2012, every day, 2.5 exabytes of data are created. A concern for large companies is to determine how to manage these data considered to be of great amplitude that affect the entire organization.

As evidenced, the characteristics of Big Data technologies favour the analysis of large volumes of data, considering in amplitude all the contexts necessary for the discovery of knowledge. Being able to apply the five characteristics of Big Data will enable organizations to be more efficient in forecasting market trends, knowledge of behaviours and attitudes to retain or prospect new customers, the definition of better strategies aimed at customers and the improvement of internal processes. The understanding of these concepts and their application result in great transformations and challenges to the business world.

2.5.1. The 5Vs of Big Data

Data is extremely important to carry out a good marketing strategy in a company, which is why the use of Big Data has become a very useful way to obtain and analyze it; has five important aspects that define the term Big Data, which are volume, velocity, variety, veracity and value. All of them are described accordingly (Hadi et al., 2015).

The volume of data varies depending on the sector or geographic location. The scale of data that is produced by people, when using their electronic or mobile devices, when they enter social networks or use other means. The data obtained for each visit to an Internet site, the use of mobile applications and other means is practically unlimited. Many technologies are emerging to manage these large volumes of data sets. Even though, it has not been beyond exabyte right now. (Patgiri & Ahmed, 2016)

Velocity is the speed with which the information is created. It is one of the main phenomena of the emergence of Big Data. Most of the information is produced in real-time, so it must be agile and fast enough to be able to capture said information and be flexible to react more efficiently by managing the immediacy of the information and being able to analyze the sequence of the information. data. With each passing day, the size of the owned data increases exponentially and this speed causes the creation of a larger database. If compression technology is used even the volume of data is constantly increasing (Tole, 2013)

Variety refers to the different forms of the data. Different data are generated daily, these are in different formats in which they are represented, having in common the heterogeneity of representation, which makes their interrelation difficult (Laney, 2001). Most of the data is generated by Internet consumption.

Veracity is the uncertainty of the data, that is, the establishment of what information is accurate and up-to-date. Due to this phenomenon, an analysis is carried out to evaluate the reliability and authenticity of the data that is collected. It is expressed as the accuracy, authenticity and significance of the available data. Large volumes of data can become problematic when an operation is desired on large data. The real question is how to believe the results obtained (Patgiri & Ahmed, 2016). Data integrity, data accuracy, the reliability of the data source and the reliability of the data are cool when it comes to data authenticity. One of the criteria for data authenticity is knowledge gain and it includes criteria such as objectivity, accuracy and reliability (Paryani, 2017). At this stage, the reality of the data is an important feature that needs to be examined in data mining, and if the information is not obtained in the right place or is unreliable, big problems may arise. For example, a marketing company may make erroneous decisions with its actual connections, which it performs with suspicious data on data authenticity (Trifu & Ivan, 2014).

Value is related to stored quality and further procedures. The enormous trash that appears in the world within itself generates information (Khan et al., 2014). TCP / IP, which includes the basic protocols of the internet every day.

Large data are stored in the records from cell phones call records. Important which of these records is valuable or not. Storing such large data will not make any sense if it is not properly managed and cannot provide insight into improvement from results (Tole, 2013).

2.5.2. Challenges in the Big Data Context

There is a consensus on the topic that the use of big data is for their analysis, which is much more powerful than just analysis of data and information from the past. Useful information for organizations can come from social networks, images, sensors, the web or other unstructured sources. This tends to significantly increase managerial challenges, in which decision-makers need to learn to ask the right questions to make tangible evidence-based decisions. To be able to analyze and extract this data, organizations need scientists who can find patterns in large data sets and translate them into useful information for their business (McAfee et al., 2012).

According to Chen, in a survey of more than 4,000 information technology (IT) professionals, in 93 countries, from 25 different industries, the IBM Tech Trends Report identified data analysis as one of the four main technological trends in the 2010s. In a survey of the state of data analysis, carried out by Bloomberg Businessweek, in 2011, it was found that 97% of companies with revenues in over $ 100 million perform in-depth data analysis using Big Data technologies (Chen et al., 2012).

In this sense, Manyika (2011) describes a forecast that by the year 2018, the United States will face a growth from 140 thousand to 190 thousand people with deep analytical skills, but there will still be a deficit of 1.5 million professionals with great analytical skills volume of data (Manyika et al., 2011). Reaffirming the context present data from Hal Varian, chief economist at Google and emeritus professor at the University of California, in which he emphasizes these emerging opportunities for IT professionals and students, as well as other professionals (Chen et al., 2012) .

Laney (2012) explains that the conventional systems of relational database management, widely used by systems in companies, do not have the adequate capacity for manipulating data in large volume (Beyer & Laney, 2012). At Big Data technologies treat data manipulation differently, with no need for structuring that data, generating savings in database systems and with large structures for processing that data on data servers. The big challenge of Big Data is the institution's capacity for statistical analysis of data and transformation of this data into useful information for the business. For some organizations, developing or finding this professional profile has been considered one of the greatest challenges, which may trigger needs for restructuring, including units for managing this data.

Among the challenges identified, in many big data implementation projects, the needs for adjustments in the internal environment of organizations are identified. In this sense, it is observed that talent management is one of the most impacted, as it needs to adapt to changes, adapting the hiring and development requirements of people within the new proposed objectives. It is also necessary to invest in new technologies and analysis software and, finally, the company's culture must reinforce the use of data in decision making (Waller & Fawcett, 2013).

The issues related to privacy are considered the most controversial today in the context of Big Data. It can be argued that when organizations act ethically, risks can be minimized with the use of cryptography tools, techniques for eliminating people's names or replacing them with pseudonyms in databases, among others.

According to Demchenko (2012), for the Information Technology sectors, this phenomenon is raising several challenges for the systems development, storage and data management teams (Demchenko et al., 2012). The author states that Big Data brings with it challenges related to new ways of collecting, processing, storing and integrating data and the database infrastructure itself needs to be restructured to cover the entire proposed context.

Waller and Fawcett (2013) reinforce that the proper exploitation of Big Data can help to improve organizational performance, but, initially, it is necessary to transform the culture of organizations and their capabilities (Waller & Fawcett, 2013). There must be an effort to transform and analyze a large volume of data into information that adds value to the business in daily operations.

As seen, the challenges for implementing Big Data analytics are many, perhaps due to the diversity of existing technologies or the various business models and strategies of organizations. Overcoming the various challenges and expanding the analysis capacity for large volumes of data, as a way to increase the capacity of relationship marketing can be considered an essential factor for companies operating in the current global market.

2.5.3. Big data, analysis and competitiveness

One of the most relevant aspects of Big Data analysis is its ability to transform available data, through statistical and computational methods, into information that is valuable to generate a competitive advantage for the company and added value to the customer. The different methods used, such as those presented in the thesis, are used to make predictions that allow better decision-making in an area where clients require more personalized attention and where this can only be offered through the forecasts of their behaviour (Ali et al., 2016).

As Porte and Hepplemann (2014) point out, the use of data, the internet of things, constitutes an opportunity to achieve new technologies that serve to enhance business and economic growth, focusing not only on cost reductions that have prevailed in the last decades, especially in the salary field but through innovations in productivity gains through big data that can modify the growth trend, which in any case requires new technical skills, clear rules on data protection and the improvement of the technological infrastructure (Porter & Heppelmann, 2014).

This change in the way of decision-making is not unique or linear, but rather raises a multitude of combinations that can determine the direction of the company allowing the adjustment of the information available to its needs, moving on to what call Data-Driven Decisions (DDD) that can serve to obtain improvements in the performance of companies, which can come from improvements in the production chain, in the structure cures of costs or in any other area where decisions can be optimized due to the existence of information flows (Brynjolfsson & McElheran, 2016).

2.6. Relationship Marketing with Big Data

Manyika et al. (2011) explain, in their report, five different ways to generate value for the business with the use of Big Data. First, making information transparent and usable at a much greater frequency. Another way would be to collect more accurate and detailed information by storing more transactional data in digital format. The third way, allowing an increasingly restricted segmentation of customers, products and services. Then, favouring decision making through sophisticated analysis. Finally, improving the development of products and services (Manyika et al., 2011).

According to Schivinski and Dabrowski (2014), social media can create a closer relationship between organizations and consumers and the involvement of both is essential for success (Schivinski & Dabrowski, 2014). As a result, marketing managers are always looking for ways to improve their communication and engagement with their consumers. Allied to this thinking, Gordon and Perrey emphasize that the impact of data analysis leads to increased precision in decision making in real-time (J. Gordon & Perrey, 2015).

For Davenport (2012), companies that understand big data will use information in real-time to understand their business environments at a more sensitive level, creating new products and services and responding to changes in usage patterns, as they occur. The volume of information that is generated on social networks such as Facebook, Twitter, Instagram, WhatsApp, LinkedIn, among others, make up the unstructured databases of the worldwide data network, in which emotions, professional preferences, consumption, political or sexual are recorded in a great history that integrates a global memory, with data that grows exponentially. In this way, working with this data and crossing information, it is possible to outline the profile of people and work out the most appropriate relationship marketing strategies for each profile, in a personalized way.

The reality of a telecommunications company in India, in which it obtained an average of five million new subscribers each month, but at the same time, lost 1.5 million customers to the competition. After a thorough analysis using big data technologies, it was identified that customers had a high tendency to switch operators after six interrupted calls. To avoid the escape of these customers, the company started to fire a torpedo with a promotion. To make the decision, the company used analysis of billions or even trillions of records or events, through big data, which allowed the company to create a customized procedure for relating to this customer profile.

Related to the retail segment, among the possible actions using big data analytics solutions are marketing based on geolocation; in-store behaviour analysis; micro-segmentation of customers; feeling analysis, strengthening the multiplatform consumer experience; price optimization; design optimization and product layout (Manyika et al., 2011).

As seen, the powerful potential of using big data analytics is evident, along with customer relationship marketing processes. Analyzes of large volumes of data make information more accurate and detailed, allowing customer segmentation, improvements in products and services, improving the effectiveness of decision-making, favouring relationships with increasingly strong and lasting customers. In this context, Demirkan and Delen (2013) still add that more effective decision-making processes are responsible for making companies more agile and efficient (Delen & Demirkan, 2013).

According to (Group, 2014), so that big data marketing can be applied in an organization, it is important to continuously develop six capacities (*GROUP '14: Proceedings of the 18th International Conference on Supporting Group Work*, 2014):

1.Opportunities: Build a culture of innovation and experimentation.

2. Trust: Establish trust among consumers, to enable wider use of their information.

3. Platform: Flexible, scalable and efficient information systems.

4. Organization: Capacity building for the implementation and relevant leverage of information applications.

5. Participation: Identification of strategic partners that can help unlock new economic opportunities.

6. Relationships: Create an open culture of support among partners and being open to sharing information.

3. THEORETICAL MODEL AND HYPOTESES

In this part of the thesis, in addition to the statements stated in the literature section, hypotheses will be made by mentioning the variables to be used in the thesis. In the thesis, the variables to be dealt with with big data online marketing are as follows: recommendation system, customer service, group influences, dynamic pricing, basic concepts such as perceived usefulness, trust, perceived risk.

3.1. Variables

The variables used in this part of the thesis and information about the variables respectively will be given.

3.1.1. Recommendation System

The recommendation system chooses specific algorithms to be used in the recommendation model, recommending typical products that are popular with your customers to new website visitors. Attribution rules automatically suggest related items you've viewed or placed in your cart. Clustering is an algorithm for grouping users or similar items together to facilitate analysis of big data matrices, and the slope predicts preferences for new items based on the average difference between a new item and other items preferred by users.

The recommendation systems are operated by famous sites such as Amazon, eBay, Trendyol, Hepsiburada, Yemeksepeti and other online websites where everything is offered. Firms that sell through online websites include a relationship between buyers and buyers in which they provide information such as hobbies and preferences while making use of both by offering a suggestion that suits their needs. Details are provided on the basics of recommendation systems: user-based collaborative filtering that uses similarities in user rankings to predict interests, and collaborative filtering elements based on items as points in a domain (Le & Liaw, 2017).

A recommendation system based on customer purchasing behaviour can evaluate product information. Study customer interests, match products and recommend substitute or complementary products to customers. Suggestion systems help individuals identify items of interest from a large collection of items by gathering input from all individuals (Resnick et al., 1997).

In these systems, recommendations are often made based on a mix of past buying or browsing behaviour, characteristics of the items considered, and shoppers' demographic and personal preference information (Shardanand & Maes, 1995). Product recommendations from other internet consumers influence consumer buying behaviour on online retailer sites (Chevalier & Mayzlin, 2006).

The online marketing recommendation system can help consumers choose their favourite products that can be applied on real networks such as Amazon, Google and other websites to encourage sales (Hongyan & Zhenyu, 2016). For these reasons, in the study, big data was taken to be examined as a variable, considering that the recommendation system will affect customer buying intention while shopping on online websites.

3.1.2. Dynamic Pricing

Dynamic pricing is an individual level price discrimination strategy where prices are applied based on customer, location, product or time (Kotler, P., Kartajaya, H., & Setiawan, 2010). Dynamic pricing, often referred to as individual price discrimination in financial terms, has become more common with the spread of Internet Marketing. Dynamic pricing is often defined as the purchase and sale of a product and sets the price of free responses to demand and supply at the level of individual transactions. So dynamic pricing can attract most sellers with the ability to use newly available information to individually adjust prices based on a particular customer's payment request (Garbarino & Lee, 2003).

Dynamic pricing is designed to maximize the profits of a retailer by manipulating the scale and timing of the price differences they use, imposing to consumers the highest prices every consumer is ready to pay. Consumers' response to this strategy has a significant impact on their satisfaction with purchases and their subsequent behavioural intentions. For example, Amazon or companies often change the price of products sold on your site by about 5%, 10%, or 15% every day, week, or month. Dynamic pricing practices in responses to segment and individual-level differences by vendors have been made more applicable as the behaviour of online customers increases (Erevelles et al., 2016).

Economic theory argues that dynamic pricing, price discrimination at the individual level is inherently good for the firm's profitability because it allows the firm to take a larger share of consumer surplus (Bolton et al., 2003). However, evidence from their experience with online websites made with internet-based dynamic pricing shows that consumers react strongly to the application. For this reason, considering that big data will have an impact on this value in the future, dynamic pricing has been taken as a variable in online shopping over websites.

3.1.3. Customer Services

Providing high-quality customer service is an important key to maintaining customer satisfaction. Big data can greatly improve your services. With in-depth data analysis, you can use your customer service to get more satisfied customers. Some customers not only complain about the products or services offered by official channels on the web, but they can also socialize with their groups. There is no such customer data, so you must be very careful with these two speedy authorities regarding customer complaints. Big data is used to improve business processes. Special applications for business process analyst in supply chain or delivery route. Depending on the geographic location and the identity of the radio frequency, sensors are used to monitor goods or delivery vehicles. This process allows your customers to track their orders. From this, customer service can be improved, and customer satisfaction can be increased.

Amazon used big data analytics to store what customers place in their virtual shopping cart. These items have recently viewed or purchased in the past. The technique used here is filtering by collaborative items. Another application is the virtual entity that allows online shoppers to interact with the shopping experience. Unlike traditional online retail, online stores have shopping information available to consumers through various channels, including product testing, product presentation or services. Virtual reality or virtual product experience allows customers to interact with products online and explore a much wider range of these products (Jian, Zhenhuı Benbasat, 2004). Previous research has shown that virtual reality has the potential to improve consumers' brand attitudes, including improving their product knowledge and purchasing intentions (Jian, Zhenhuı Benbasat, 2004).

Customer opinion is the feedback of a product or service made by the purchasing consumer. It evaluates and comments on the quality of the product or service rather than professional reviews on the website. Interested customers can see feedback from previous customers who previously interacted with the website. This service can guarantee the reliability of product buyers. They can also inspire other customers to share their thoughts on the products sold.

As can be understood from the above paragraphs, customer services are defined as a variable considering that it will influence customer buying intention and on big data and online shopping.

3.1.4. Group Influences

Consumers are influenced by the groups they are emotionally affected by and to which they feel belong. Group effects can cause a client to change their mindset with a review group. Sometimes consumers are shy about brands they believe will include them in a group they don't want to include. They tend to buy the help people create and suggestions from like-minded people. An individual choice may vary according to social networks influenced by group feeling. Consumers post their feedback after purchasing a product or service on the website. Feedbacks are not considered to be fake online marketing (Ahmad et al., 2014). It has a strong perception in the human mind for strong and social communication. Customer reviews are a way to share thoughts, ideas, beliefs and experiences among customers. The mix of positive and negative reviews allows consumers to spend time reading them and influences the customers' decision. In a study by Germany and Mirza (2013), online shoppers are influenced by groups, and a larger percentage of them are addicted to making product purchasing decisions (Almana & Mirza, 2013). Negative groups have a stronger negative effect than positive groups (Ahmad et al., 2014). For this reason, in this study, it was defined as a variable, considering that it is related to big data and will have an effect on customer buying intention.

3.1.5. Perceived Usefulness

Perceived usefulness means that online purchasers think that using this system on an individual basis can improve their business performance. There are many areas currently investigating the impact of perceived usefulness. In the introduction of technology, Snchez and Hueros (2010) found that perceived usefulness can affect the user purchasing approach and that user behaviour has an impact on new technologies (Sánchez & Duarte-Hueros, 2010). By applying the gap theory in library management, Wang and Guan (2010) confirmed that perceived usefulness plays an important role in improving the service quality of the university library through empirical analysis in three aspects of service quality, information quality and online system quality (Wang Y, 2010). Koufaris and Hampton (2002) explained the effect of environmental psychology on the consumer in the field of online shopping. They thought that perceived usefulness had a more significant impact on online shopping consumer behaviour than other factors (Koufaris & Hampton-Sosa, 2002). From the studies of previous people, we can find that the main determinant is perceived as the use of consumers regardless of whether they are willing to adopt a new information systems or technology. For this reason, perceived usefulness is defined as a variable, considering that it may be one of the variables in big data.

3.1.6. Perceived Risk

Raymond Bauer, professor of Harvard University; tried to define the concept of risk in 1960. He believed that perceived risk would lead to its unpredictable consequences of any purchasing behaviour of consumers (Bauer, 1960). In addition, Wang thought that according to the expectation theory, perceived risk is the expectations of consumers to endure their loss with a predictable outcome (Wang & Emurian, 2005). Information confusion often arises when shopping on online websites. This information confusion puts the consumer at a disadvantage when shopping online and causes their decisions to face many risks and uncertainties. Featherman and Pavlou (2003) investigated the situation of consumers shopping online through six dimensions of social risk, privacy risk, economic risk, time risk, performance risk and psychological risk (Featherman & Pavlou, 2003). Doolin and Stuart (2005) also confirmed the relationship between the perceived risk of online shopping and consumer behaviour decision through empirical studies (Doolin et al., 2005). Therefore, this research considers perceived risk as one of the variables to investigate consumer purchasing intention in the background of big data.

3.1.7. Trust

Shopping on newly emerging online websites, more and more people are paying attention to trust. Trust is the consumer's perception of business commitments and the consumer's awareness of business-related honest behaviour. Lee and Turban (2010) confirmed the trust trend of consumers together with three factors, safety factor, online shopping environment and reliability of online businesses (King et al., 2010) . Walczuch and Lundgren (2004) investigate psychological determinants of online shopping trust of consumers, including those based on perception factors, experience factors, and knowledge factors (Walczuch & Lundgren, 2004) . Gordon (2006) pointed out that customer trust is a key factor in the success of mobile e-commerce (N. Gordon & Brayshaw, 2006) . For this reason, trust is considered as one of the intermediate variables to investigate consumer purchase intention in the background of big data in this study.

3.1.8. Customer Buying Intention

Amazon uses Big Data analytics to record what customers place in their virtual shopping cart. These items carefully interpret past purchases. The technique used here is collaborative filtering from item to item. Another application is the virtual entity that allows online shoppers to interact with the shopping experience. Unlike traditional online retail, online shopping has recommended shopping information to consumers through a variety of channels, including product trial, product presentation, customer service, ease of use, or services. Virtual reality, offered services, dynamic price changes, group influence on sites or virtual product experience allow customers to interact with online products and experience a much wider range of these products (Jian, Zhenhuı Benbasat, 2004) . In previous exploratory studies, it has been suggested that many of the data of consumers are determinative to improve purchase intentions (Daugherty et al., 2005; Jian, Zhenhuı Benbasat, 2004). For this reason, the research has taken the buying intention as the variable and its relationship with the dependent variables has been investigated.

3.2. Hypotheses

Hypotheses can be set up as follows according to the variables specified above.

H1a: The recommendation system of the website significantly affects the perceived usefulness.

H1b: Customer services of the website significantly affect the perceived usefulness.

H1c: Group influences on the website significantly affect the perceived usefulness.

H1d: Dynamic pricing on the website significantly affects the perceived usefulness.

H2a: The recommendation system of the website significantly affects the perceived risk.

H2b: Customer services of the website significantly affect the perceived risk.

H2c: Group influences on the website significantly affect the perceived risk.

H2d: Dynamic pricing on the website significantly affect the perceived risk.

H3a: The recommendation system of the website significantly affects trust.

H3b: Customer services of the website significantly affect trust.

H3c: Group influences on the websites significantly affect trust.

H3d: Dynamic pricing on the website significantly affect trust.

H3e: Perceived usefulness of the website significantly affect trust.

H3f: Perceived risk of the website significantly affect trust.

H4a: Perceived usefulness of the website significantly affect the customer buying intention.

H4b: Perceived risk of the website significantly affect the customer buying intention.

H4c: Trust of the website significantly affect the customer buying intention.

3.2.1. Research Model

According to the hypotheses, the research model can be established as follows.

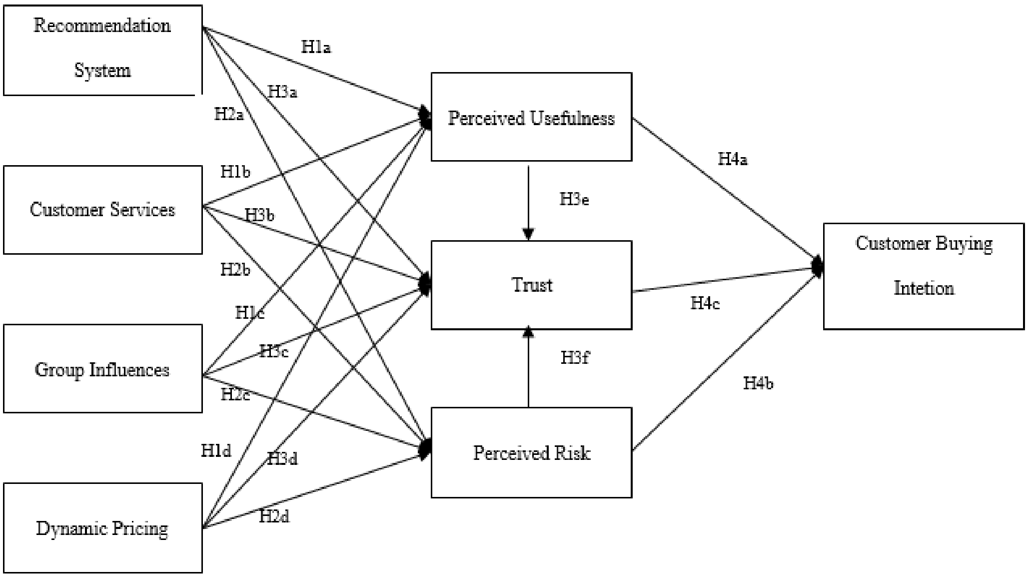

Figure 1: Research Model

4. RESEARCH METHOD

The primary purpose of this chapter is to describe and define the procedure and methods that were employed for this study. It also includes the pre-test part, strategy of the study and methods used to gather data about the research survey. This study utilizes a structured survey that focuses on the relationships among eight variables in the research study; which are recommendation system (RS), customer services (CS), group influences (GI), awareness of dynamic pricing (DP), perceived risk (PR), trust (T), perceived risk (PU) and customer buying intention (PI).

4.1.1. Questionnaire Design

The survey questions taken from these studies are given in detail in the table below. Also, Lee and Liaw's (2017) and Tang and Wu's (2015) studies are beneficial to clarify the variables and related questions (Le & Liaw, 2017; Min & Zhong, 2015). The questionnaire includes 7-point Likert-type scales whose items are adapted from various consumers. Items were measured on a scale of 1 (strongly disagree) to 7 (strongly agree). This criterion has been advanced by the work of Tang and Wu (2015).

Participants were asked about the latest shopping website and product category. Survey questions are presented in 3 sections. In the first section, 4 explanations and 2 questions about the last shopping site and product category, 12 statements in the second section, 13 statements in the third section, and 7 demographic questions were presented to the participants for evaluation.

A statement of 29 items with 7 Likert was requested, and an explanation about their last shopping place.

Table 1: Constructs in the study and their sources

Construct	Source	Questions
Customer buying Intention	(Ehrenberg, 2000) (Lee et al., 2013)	4
Recommendation System (RS)	(Min & Zhong, 2015)	4
Customer Services (CS)	(Min & Zhong, 2015)	4
Group Influences (GI)	(Almana & Mirza, 2013)	4
Dynamic Pricing (DP)	(Le & Liaw, 2017)	3
Perceived Risk (PR)	(Min & Zhong, 2015)	4
Perceived Risk (PU)	(Min & Zhong, 2015)	3
Trust (T)	(Min & Zhong, 2015)	3

4.1.2. Method of Data Collection

A survey was conducted using primary data. The survey was shared on the web between 25.08.2020 and 25.09.2020. The survey was applied to citizens living in Istanbul, Ankara, Izmir, Antalya Isparta in 2020. The questionnaire was put on the internet and citizens living in Istanbul were asked to fill out the questionnaire.

The data collection tool was a structured questionnaire developed in Google Forms. The questionnaire is designed based on a literature review for research objectives. Before the main work, any wording errors misunderstood points, etc. 25 respondents the pilot study has been conducted to find out if it exists. Based on the feedback from the pilot study, necessary changes were made to the questionnaire. The survey was distributed to different demographic groups of people with a variety of backgrounds.

4.2. Sampling

The convenience sampling method as one of the non-probabilistic sampling methods is chosen. Data collection was carried out over 1 month, 25.08.2020 and 25.09.2020, with a sample size of 336 people living in Istanbul, Ankara, Izmir, Antalya Isparta.

5. FINDINGS

The main results of the analysis are presented in this section, which consists of three sections. First, sample profile and descriptive statistics were summarized. Second, the results of reliability for each aspect are explained. Finally, the results of the regression analysis explore the relationship between the assumptions and the structures of the model. The last part is designed to indicate the statistically significant differences between variables according to demographical variables.

To identify the importance of predetermined relationships and effects, SPSS version 24.0. was used. It was selected based on statistical methods. measurement scales and type of subject analyzed; Correlation analysis, Regression Analysis and Analysis of Variance (ANOVA).

5.1. Descriptive Findings

The survey was conducted with 336 respondents with different backgrounds and demographics in various cities in Turkey. None of the questionnaires had missing data therefore all the responses were valid. The results of the descriptive analysis for the sample are demonstrated in the following tables. According to Table 2, 58.0% of participants were male, and 39.9% were females. 2.1% of participants preferred not to say their gender.

Table 2: Sample Profile According to Gender

Gender	Frequency (n)	Percent (%)
Male	195	58.0
Female	134	39.9
Prefer not to say	7	2.1
Total	336	100

Descriptive statistics about participants ages is shown in Table 3. 11.0% of participants had 18-24, 29.2% had 25-34, 19.6% had 35-44, 19.9% had 45-54 and 20.2% had over 55 ages.

Table 3: Sample Profile According to Age

Age	Frequency (n)	Percent (%)
18-24	37	11.0
25-34	98	29.2
35-44	66	19.6
45-54	67	19.9
Over 55	68	20.2

According to Table, 4,1.5% of participants had less than a high school diploma, 14.6% had high school level education, 65.8% had bachelor’s degree, 14.6% had master’s degree, 2.7% had doctorate.

Table 4 : Sample Profile According to Education

Education	Frequency (n)	Percent (%)
Less than a high school diploma	5	1.5
High school degree or equivalent	49	14.6
Bachelor`s degree	221	65.8
Master`s degree	49	14.6
Doctorate	9	2.7
Other	3	0.9

As given in Table 5, 30.4% of participants were single, 60.7% were married, 6.0% were divorced, and 3.0% were a widow.

Table 5: Sample Profile According to Marital Status

Household income	Frequency (n)	Percent (%)
Below 2k TL.	30	8.9
2001-6k TL	181	53.9
6001-10k TL	76	22.6
Above 10001 TL	49	14.6

Income distribution of the participants as given in Table 6. 8.9% of participants had below 2.000 TL income, 53.9% had 2001-6.000 TL, 22.6% had 6.001-10.000 TL and 14.6% had over 10.000 TL monthly income.

Table 6: Sample Profile According to Income Level

Household income	**Frequency (n)**	**Percent (%)**
Below 2k TL.	30	8.9
2001-6k TL	181	53.9
6001-10k TL	76	22.6
Above 10001 TL	49	14.6

The most common item for online shopping was clothing with a 43.2% rate, followed by electronics, tools and hardware. 21.7% of participants stated that they prefer online shopping a below 10% rate, 28.3% of participants prefer 10%-30% rate, 28.6% of participants prefer 30%-60% rate, 17.9% of participants prefer 60%-80% rate, and 3.6% of participants prefer 80% and above rate online shopping. As can be seen from Table 7 the online shopping characteristics of participants.

Table 7: Online shopping characteristics

	Frequency (n)	Percent
Online shopping types		
Apparel / Clothing	145	43.2
Electronics	51	15.2
Tools and Hardware (Home, Kitchen, Garden etc.)	43	12.8
Books	35	10.4
Other	18	5.4
Cosmetics & Personal Care	17	5.1
Food	16	4.8
Pet Accessories	6	1.8
Sports Equipment and Apparel	4	1.2
Games & Game Consoles	1	0.3
Total	336	100
Below %10	73	21.7
%10-%30	95	28.3
%30-%60	96	28.6
%60-%80	60	17.9
%80-Above	12	3.6
Total	336	100

5.1.1. Descriptive Statistics for Customer Buying Intention

This section of the questionnaire will show the distribution of respondents' responses to customer buying intention statements. In addition, each statement is aggregated and specified as customer buying intention (PI) as a single variable. There are 4 items on the scale. Participants were asked to answer their statements on a 7-point Likert scale. (1: Strongly Disagree, 7: Strongly Agree). The average response to each statement is shown in the table.

Table 8: Mean Values of Customer Buying Intention Statements

	Minimum	Maximum	Mean	Std Deviation
I would like to do my shopping through websites. (PI1)	1	7	5.00	1.599
I will continue to do my shopping through the websites. (PI2)	1	7	5.15	1.581
I take action to buy from websites (PI3)	1	7	4.95	1.729
I recommend the shopping from the website to my friends and family. (PI4)	1	7	5.28	1.589

5.1.2. Descriptive statistics for Recommendation System (RS)

This section of the questionnaire will show the distribution of respondents' responses to recommendation system statements. In addition, each statement is aggregated and specified as Recommendation System (RS) as a single variable. There are 4 items on the scale. Participants were asked to answer their statements on a 7-point Likert scale. (1: Strongly Disagree, 7: Strongly Agree). The average response to each statement is shown in the table.

Table 9: Mean Values of Recommendation System Statements

	Minimum	Maximum	Mean	Std. Deviation
Online shopping sites can offer replacement products for the product i want to buy. (RS1)	1	7	4.67	1.967
Online shopping sites can offer complementary products for the product ı want to buy. (RS2)	1	7	5.04	1.823
Online shopping sites can recommend products that i might like or the site’s bestselling (RS3)	1	7	5.35	1.614
I believe that the advice provided by online shopping sites is a courtesy. (RS4)	1	7	4.28	2.015
Valid N (listwise) = 336				

5.1.3. Descriptive statistics for Customer Services (CS)

This section of the questionnaire will show the distribution of respondents' responses to customer services statements. In addition, each statement is aggregated and specified as Customer Services (CS) as a single variable. There are 4 items on the scale. Participants were asked to answer their statements on a 7-point Likert scale. (1: Strongly Disagree, 7: Strongly Agree). The average response to each statement is shown in the table.

Table 10: Mean Values of Customer Services Statements

	Minimum	Maximum	Mean	Std. Deviation
Online shopping sites offer a channel (contact number, email etc.) to support customers (CS1)	1	7	5.04	1.653
I expect my order to be tracked in online shopping (CS2)	1	7	6.51	1.162
The shopping site providing virtual experience can enable me to choose more suitable products (CS3)	1	7	5.69	1.472
I can refer to comments from customers who have previously purchased the products (CS4)	1	7	6.20	1.293
Valid N (listwise) = 336				

5.1.4. Descriptive statistics for Group Influences (GI)

This section of the questionnaire will show the distribution of respondents' responses to group influences statements. In addition, each statement is aggregated and specified as Group Influences (GI) as a single variable. There are 4 items on the scale. Participants were asked to answer their statements on a 7-point Likert scale. (1: Strongly Disagree, 7: Strongly Agree). The average response to each statement is shown in the table.

Table 11 Mean Values of Group Influences Statements

	Minimum	Maximum	Mean	Std. Deviation
When I want to purchase a product online, the reviews offered on the website help me make my decision. (GI1)	1	7	6.00	1.407
Comments posted on the website affect the purchase decision. (GI2)	1	7	6.03	1.314
The way others evaluate how well other product reviews have worked influences my purchase decision. (GI3)	1	7	5.98	1.286
The popularity of the website that offers comments or reviews influences my purchase decision. (GI4)	1	7	5.89	1.400
Valid N (listwise) = 336				

5.1.5. Descriptive statistics for Dynamic Pricing (DP)

This section of the questionnaire will show the distribution of respondents' responses to dynamic pricing statements. In addition, each statement is aggregated and specified as Dynamic Pricing (DP) as a single variable. There are 3 items on the scale. Participants were asked to answer their statements on a 7-point Likert scale. (1: Strongly Disagree, 7: Strongly Agree). The average response to each statement is shown in the table.

Table 12: Mean Values of Dynamic Pricing Statements

	Minimum	Maximum	Mean	Std. Deviation
I know that shopping websites collect personal data through cookies. (DP1)	1	7	5.86	1.532
I know that shopping sites use the information collected for personalized product samples and advertisements (DP2)	1	7	6.04	1.324
I know that shopping websites use the information collected to change the price of products. (DP3)	1	7	5.19	1.699
Valid N (listwise) = 336				

5.1.6. Descriptive statistics for Perceived Risk (PR)

This section of the questionnaire will show the distribution of respondents' responses to perceived risk statements. In addition, each statement is aggregated and specified as Perceived Risk (PR) as a single variable. There are 4 items on the scale. Participants were asked to answer their statements on a 7-point Likert scale. (1: Strongly Disagree, 7: Strongly Agree). The average response to each statement is shown in the table.

Table 13: Mean Values of Perceived Risk Statements

	Minimum	Maximum	Mean	Std. Deviation
When I see reviews of problems with the shopping website, I don’t buy anything from site. (PR1)	1	7	5.32	1.658
I prefer shopping on the website as I think it is low risk. (PR2)	1	7	4.81	1.726
When shopping online, I worry about my account information being stolen by viruses or hackers. (PR3)	1	7	5.58	1.680
I feel the risk when shopping online (PR4)	1	7	5.11	1.742
Valid N (listwise) = 336				

5.1.7. Descriptive statistics for Perceived Usefulness (PU)

This section of the questionnaire will show the distribution of respondents' responses to perceived risk statements. In addition, each statement is aggregated and specified as Perceived Usefulness (PU) as a single variable. There are 3 items on the scale. Participants were asked to answer their statements on a 7-point Likert scale. (1: Strongly Disagree, 7: Strongly Agree). The average response to each statement is shown in the table.

Table 14: Perceived Usefulness

	Minimum	**Maximum**	**Mean**	**Std. Deviation**
Time and money can be saved with online shopping (PU1)	1	7	5.91	1.347
I can have fun and enjoy the time when I use shopping through the website (PU2)	1	7	5.19	1.688
Online shopping is very useful to me. (PU3)	1	7	5.21	1.560
Valid N (listwise) = 336				

5.1.8. Descriptive statistics for Trust (T)

This section of the questionnaire will show the distribution of respondents' responses to trust statements. In addition, each statement is aggregated and specified as Trust (T) as a single variable. There are 3 items on the scale. Participants were asked to answer their statements on a 7-point Likert scale. (1: Strongly Disagree, 7: Strongly Agree). The average response to each statement is shown in the table.

Table 15: Table 8 Mean Values of Trust Statements

	Minimum	Maximum	Mean	Std. Deviation
I think shopping on websites is safe. (T1)	1	7	4.70	1.517
Websites' operation with reputable and reliable suppliers will affect their adoption by consumers. (T2)	2	7	6.22	1.084
I am comfortable when I shop from websites. (T3)	1	7	5.03	1.489
Valid N (listwise) = 336				

5.2. Reliability of Scales

The reliability of the survey items including 8 scales has been checked by Cronbach's Alpha.

Table 16: Reliability analysis results of scale and dimensions

Code	Dimension	Number of items	Cronbach Alpha
PI	Customer Buying Intention	4	0.936
GI	Group Influences	4	0.869
CS	Customer Services	4	0.713
RS	Recommendation System	4	0.775
PR	Perceived Risk	3 (item 2 removed)	0.607
PU	Perceived Risk	3	0.796
T	Trust	3	0.668
DP	Awareness about Dynamic Pricing	3	0.793

The Cronbach Alpha value of the Perceived Risk Scale is 0.936 and is greater than 0.7. As seen in Table 16, this result shows that each item in this scale is consistent. the other to measure Customer Buying Intention. See Annex B, Table B1 for detailed information. information and SPSS results.

The Cronbach Alpha value of the Perceived Risk Scale is 0.869 and is greater than 0.7. As seen in Table 16, this result shows that each item in this scale is consistent. the other to measure Group Influences. See Annex B, Table B2 for detailed information.

information and SPSS results.

The Cronbach Alpha value of the Customer Services Scale is 0.713 and is greater than 0.7. As seen in Table 16, this result shows that each item in this scale is consistent. the other to measure Customer Services. See Annex B, Table B3 for detailed information. information and SPSS results.

The Cronbach Alpha value of the Recommendation System Scale is 0.775 and is greater than 0.7. As seen in Table 16, this result shows that each item in this scale is consistent with the other to measure Recommendation System. See Annex B, Table B4 for detailed information. information and SPSS results.

The Cronbach Alpha value of the Perceived Risk Scale is 0.607 and is almost 0.7 (J. F. Hair et al., 1995; Moss et al., 1998). As seen in Table 16, this result shows that each item in this scale is consistent with the other to measure Perceived Risk. After scale, if item deleted analysis, item 2 was removed from the dimension. When the alpha was calculated with PR2, its values was 0.412, so it was removed. See Annex B, Table B5 for detailed information. information and SPSS results.

The Cronbach Alpha value of the Perceived Risk Scale is 0.796 and is greater than 0.7. As seen in Table 16, this result shows that each item in this scale is consistent the other to measure Perceived Risk. See Annex B, Table B6 for detailed information. information and SPSS results.

The Cronbach Alpha value of the Trust Scale is 0.668 and is almost 0.7. As seen in Table 16, this result shows that each item in this scale is consistent with the other to measure Trust. See Annex B, Table B7 for detailed information. information and SPSS results.

The Cronbach Alpha value of the Dynamic Pricing Scale is 0.668 and is almost 0.7.

As seen in Table 16, this result shows that each item in this scale is consistent with the other to measure Dynamic Pricing. See Annex B, Table B8 for detailed information. information and SPSS results.

5.3. Normality Tests

According to George and Mallary (2010), the values for asymmetry and kurtosis need to lie between -2 and +2 to prove normal univariate distribution (D. George & Mallery, 2010) . According to the table, CS2 and CS4 seem problematic, however, due to relatively high sample size, these would be neglected.

Table 17: Skewness and Kurtosis Values

Variables	Skewness	Kurtosis
PI1	-.551	-.329
PI2	-.625	-.302
PI3	-.604	-.525
PI4	-.781	-.162
RS1	-.472	-.866
RS2	-.731	-.375
RS3	-.869	.082
RS4	-.147	-1.200
CS1	-.588	-.326
CS2	-2.923	8.941
CS3	-1.052	.489
CS4	-2.015	4.121
GI1	-1.703	2.761
GI2	-1.525	2.378
GI3	-1.577	2.808
GI4	-1.423	1.718
DP1	-1.376	1.271
DP2	-1.466	1.874
DP3	-.623	-.423
PR1	-.620	-.512
PR2	-.486	-.437
PR3	-1.052	.126
PR4	-.705	-.465
PU1	-1.150	.653
PU2	-.741	-.245
PU3	-.592	-.358
T1	-.410	-.230
T2	-1.282	.814
T3	-.614	-.077

5.4. Hypothesis Testing

In that section, established hypotheses are tested.

5.4.1. Hypotheses Set 1: Relation between Perceived Usefulness Web Site Base Parameters

Pearson correlation was applied because of normality tests. Correlations between each parameter are shown below the table.

Table 18: Correlations PU, RS, CS, GI, DP

		PU	RS	CS	GI	DP
Pearson Correlation	PU	1,000	,372	,520	,448	,183
	RS	,372	1,000	,479	,392	,092
	CS	,520	,479	1,000	,660	,208
	GI	,448	,392	,660	1,000	,157
	DP	,183	,092	,208	,157	1,000
Sig. (1-tailed)	PU	.	,000	,000	,000	,000
	RS	,000	.	,000	,000	,046
	CS	,000	,000	.	,000	,000
	GI	,000	,000	,000	.	,002
	DP	,000	,046	,000	,002	.
N	PU	336	336	336	336	336
	RS	336	336	336	336	336
	CS	336	336	336	336	336
	GI	336	336	336	336	336
	DP	336	336	336	336	336

According to the significance level (α), it is seen that there is a positive correlation with perceived usefulness, recommendation system, customer services, group influences, dynamic pricing. Between perceived usefulness and other data according to p values:

Correlation with perceived usefulness between all measured data on the above table is significant. ($p<0.01$)

Table 19: Regression Values For PU, RS, CS, GI, DP

Variable	B	Standard Error	β	t	p	VIF	Durbin-Watson
Constant	,857	,410		2,089	,037		2,125
Recommendation System	,130	,047	,144	2,758	,006	1,316	
Customer Services	,411	,081	,327	5,062	,000	2,008	
Group Influences	,185	,069	,163	2,673	,008	1,795	
Dynamic Pricing	,077	,047	,076	1,626	,105	1,046	
R: 0,558 R^2: 0,311 Adjusted R^2: 0,303 F: 37,337 p: 0,000 Dependent Variable: PU Independent Variables: RS, CS, GI, DP							

The regression analysis cloud made to determine the variables affecting the PU variable is presented in Table 20. The PU variable of the regression model was included as the variable, and the variables RS, CS GI, and DP as independent variables. When examined in the regression model, it is seen that the model is significant (F = 37.337; p = 0.000), independent variables explain 30.3% of the total variance in the PU variable, VIF values and Durbin Watson value do not pose a problem (Hair et al., 2010). According to the analysis findings, the PU variable of RS (β = 0.144; p = 0.006), CS (β = 0.327; p = 0.000) and GI (= 0.163; p = 0.008) It was determined that they have a positive and significant effect on.

Hypothesis interpretations according to p values are as follows:

Table 20: Perceived Usefulness Hypotheses

Hypothesis	p values	Comment
H1a: RS – PU	**,006**	Not Rejected
H1b: CS – PU	**,000**	Not Rejected
H1c: GI – PU	**,008**	Not Rejected
H1d: DP – PU	,105	Rejected

5.4.2. Hypotheses Set 2: Relation between Perceived Risk Web Site Base Parameters

Pearson correlation was applied. Correlations between each parameter are shown below the table.

Table 21: Correlations PR, RS, CS, GI, DP

		PR	RS	CS	GI	DP
Pearson Correlation	PR	1,000	,084	,046	,129	,140
	RS	,084	1,000	,479	,392	,092
	CS	,046	,479	1,000	,660	,208
	GI	,129	,392	,660	1,000	,157
	DP	,140	,092	,208	,157	1,000
Sig. (1-tailed)	PR	.	,061	,201	,009	,005
	RS	,061	.	,000	,000	,046
	CS	,201	,000	.	,000	,000
	GI	,009	,000	,000	.	,002
	DP	,005	,046	,000	,002	.
N	PR	336	336	336	336	336
	RS	336	336	336	336	336
	CS	336	336	336	336	336
	GI	336	336	336	336	336
	DP	336	336	336	336	336

According to the correlation values, it is seen that there is a few positive correlations ($r>0$) with perceived risk, recommendation system, customer services, group influences, dynamic pricing.

Between perceived risk and other data’s according to p values:

Correlation with perceived risk between all measured data on the above table is not too significant. (p<0.01)

Table 22: Regression Analyses Values For PR, RS, CS, GI, DP

Variable	**Unstandardized Coefficient B**	**Unstandardized Coefficient Standard Error**	**Standardized Coefficient β**	**t**	**p**	**VIF**	**Durbin-Watson**
Constant	4,101	,474		8,661	,000		2,068
Recommendation System	,059	,054	,066	1,075	,283	1,316	
Customer Services	-,148	,094	-,120	-1,575	,116	2,008	
Group Influences	,179	,080	,162	2,241	**,026**	1,795	
Dynamic Pricing	,132	,054	,133	2,418	**,016**	1,046	
R: 0,199 R^2: 0,040 Adjusted R^2: 0,028 F: 3,415 p: 0,009 Dependent Variable: PR Independent Variables: RS, CS, GI, DP							

The regression analysis findings made to determine the variables affecting the PR variable are presented in Table 23. In the regression model, the PR variable is included as dependent variables, and the RS, CS, GI, and DP variables are included as independent variables. When the findings regarding the regression model are examined, it is seen that the model is significant (F = 3.415; p = 0.009), independent variables explain 2.8% of the total variance in the PR variable, VIF values and Durbin Watson value do not pose a problem. (J. Hair et al., 2010) According to the analysis findings, it was determined that the variables GI (= 0.162; p = 0.026) and "Dynamic Pricing" (= 0.133; p = 0.016) had a significant positive effect on the PR variable. Hypothesis interpretations according to p values are as follows:

Table 23: Perceived Risk Hypotheses

Hypothesis	p values	Comment
H2a: RS – PR	,283	Rejected
H2b: CS – PR	,116	Rejected
H2c: GI – PR	,026	Not Rejected
H2d: DP – PR	,016	Not Rejected

5.4.3. Hypotheses Set 3: Relation between Trust and Web Site Base Parameters

According to the result of Pearson correlation analysis *N*, *r* and *p* values can be seen in the table below.

Table 24: Correlations T, RS, CS, GI, DP, PR, PU

		T	RS	CS	GI	DP	PR	PU
Pearson Correlation	T	1,000	,353	,393	,367	,195	-,177	,615
	RS	,353	1,000	,479	,392	,092	,084	,372
	CS	,393	,479	1,000	,660	,208	,046	,520
	GI	,367	,392	,660	1,000	,157	,129	,448
	DP	,195	,092	,208	,157	1,000	,140	,183
	PR	-,177	,084	,046	,129	,140	1,000	-,040
	PU	,615	,372	,520	,448	,183	-,040	1,000
Sig. (1-tailed)	T	.	,000	,000	,000	,000	,001	,000
		,000	.	,000	,000	,046	,061	,000
	CS	,000	,000	.	,000	,000	,201	,000
	GI	,000	,000	,000	.	,002	,009	,000
	DP	,000	,046	,000	,002	.	,005	,000
	PR	,001	,061	,201	,009	,005	.	,234
	PU	,000	,000	,000	,000	,000	,234	.
N	T	336	336	336	336	336	336	336
	RS	336	336	336	336	336	336	336
	CS	336	336	336	336	336	336	336
	GI	336	336	336	336	336	336	336
	DP	336	336	336	336	336	336	336
	PR	336	336	336	336	336	336	336
	PU	336	336	336	336	336	336	336

According to the correlation values, it is seen that there is a positive correlation ($r>0$) with trust, recommendation system, customer services, group influences, dynamic pricing and perceived usefulness, but there is a negative correlation with perceived risk ($r<0$).

Between trust and other data’s according to p values:

Correlation with trust between all measured data on the above table is significant. ($p<0.01$)

Table 25: Regression Analyses Values For T, PU, PR, RS, CS, GI, DP

Variable	Unstandardized Coefficient B	Unstandardized Coefficient Standard Error	Standardized Coefficient β	t	p	VIF	Durbin-Watson
Constant	2,475	,341		7,248	,000		1,888
Recommendation System	,105	,036	,141	2,955	,003	1,354	
Customer Services	-,019	,063	-,019	-,310	,757	2,169	
Group Influences	,104	,052	,112	1,985	,048	1,870	
Dynamic Pricing	,088	,035	,106	2,474	,014	1,076	
Perceived Risk	-,167	,036	-,198	-4,682	,000	1,057	
Perceived Usefulness	,408	,041	,495	9,918	,000	1,473	

R: 0,666 R^2: 0,444 Adjusted R^2: 0,434 F: 43,728
p: 0,000
Dependent Variable: T
Independent Variables: PU,PR,RS, CS, GI, DP

The regression analysis findings made to determine the variables that affect the T variables are presented in Table 26. In the regression model, the T variable, the dependent variable, RS, CS, GI, DP, PR, and PU variables were included as independent variables. When the findings regarding the regression model are examined, it is seen that the model is significant (F = 43.728; p = 0.000), independent variables explain 43.4% of the total variance in the T variable, and VIF values and Durbin Watson value do not pose a problem. (J. Hair et al., 2010) According to the analysis findings, RS (β = 0.141; p = 0.003), GI (β = 0.112; p = 0.048), DP (β =

0.106; p = 0.014) and PU (β = 0.495; p = 0.000) variables have a positive significant effect on the T variable, and PR (β = -0.198; p = 0.000) variables have a significant negative effect.

Hypothesis interpretations according to p values are as follows:

Table 26: Perceived Risk Hypotheses

Hypothesis	p values	Comment
H3a: RS – T	,003	Not Rejected.
H3b: CS – T	,757	Rejected.
H3c: GI – T	,048	Not Rejected.
H3d: DP – T	,014	Not Rejected.
H3e: PU – T	,000	Not Rejected.
H3f: PR – T	,000	Not Rejected.

5.4.4. Hypotheses Set 4: Relation between Customer Buying Intention, Trust, Perceived Usefulness and Perceived Risk

According to the result of Pearson correlation analysis *N*, *r* and *p* values can be seen in the table below.

Table 27: Correlations PI, PR, PU, T

Correlations					
		PI	PR	PU	T
Pearson Correlation	PI	1,000	-,086	,598	,535
	PR	-,086	1,000	-,040	-,177
	PU	,598	-,040	1,000	,615
	T	,535	-,177	,615	1,000
Sig. (1-tailed)	Customer Buying Intention	.	,059	,000	,000
	PR	,059	.	,234	,001
	PU	,000	,234	.	,000
	T	,000	,001	,000	.
N	PI	336	336	336	336
	PR	336	336	336	336
	PU	336	336	336	336
	T	336	336	336	336

According to the correlation values, it is seen that there is a positive correlation between customer buying intention ($r>0$) and perceived usefulness and trust, but there is a negative correlation with perceived risk ($r<0$).

Between customer buying intention and other data’s according to p values:

Correlation with perceived risk is insignificant. ($p>0.01$)

Correlation with trust and perceived risk is significant. ($p<0.01$)

Table 28: Regression Analyses Values For PI, T, PU, PR

Variable	Unstandardized Coefficient B	Unstandardized Coefficient Standard Error	Standardized Coefficient β	t	p	VIF	Durbin-Watson
Constant	,556	,462		1,204	,230		2,121
Perceived Risk	-,025	,051	-,021	-,496	,620	1,041	
Perceived Usefulness	,500	,062	,435	8,056	**,000**	1,621	
Trust	,368	,076	,264	4,812	**,000**	1,671	
R: 0,635	R^2: 0,403	Adjusted R^2: 0,398	F: 74,723	p: 0,000			
Dependent Variable: PI							
Independent Variables: T, PU, PR							

The regression analysis findings made to determine the variables affecting the PI variable are presented in Table 29. PI variable, PR, PU and T variables were included as independent variables in the regression model. When the findings regarding the regression model are examined, it is seen that the model is significant (F = 74,723; p = 0,000), independent variables explain 39.8% of the total variance in the PI variable, VIF values and Durbin Watson value do not pose a problem. (J. Hair et al., 2010) According to the analysis findings, it was determined that PU (β = 0.435; p = 0.000) and T (β = 0.264; p = 0.000) variables had a significant positive effect on the PI variable.

Hypothesis interpretations according to p values are as follows:

Table 29: Trust Hypotheses

Hypothesis	p values	Comment
H4a: PU – PI	**,000**	Not Rejected
H4b: PR – PI	,620	Rejected
H4c: T– PI	**,000**	Not Rejected

5.4.5. Hypotheses Sets Summaries

Evaluation comments on the hypotheses are given in the table below.

Table 30: Hypotheses Sets Summaries

Hypothesized content	Level ρ	Result
H1a: The recommendation system of the website significantly affect the perceived usefulness.	,006	Not Rejected.
H1b: Customer services of the website significantly affect the perceived usefulness.	,000	Not Rejected.
H1c: Group influences on the website significantly affect the perceived usefulness.	,008	Not Rejected.
H1d: Dynamic pricing on the website significantly affects the perceived usefulness.	,105	Rejected.
H2a: The recommendation system of the website significantly affects the perceived risk.	,283	Rejected.
H2b: Customer services of the website significantly affect the perceived risk.	,116	Rejected.
H2c: Group influences on the website significantly affect the perceived risk.	,026	Not Rejected.
H2d: Dynamic pricing on the website significantly affect the perceived risk.	,016	Not Rejected.
H3a: The **r**ecommendation system of the website significantly affect trust.	,003	Not Rejected.
H3b: Customer services of the website significantly affect trust.	,757	Rejected.
H3c: Group influences on the websites significantly affect trust.	,048	Not Rejected.
H3d: Dynamic pricing on the website significantly affect trust.	,014	Not Rejected.
H3e: Perceived usefulness of the website significantly affect trust.	,000	Not Rejected.
H3f: Perceived risk of the website significantly affect trust.	,000	Not Rejected.
H4a: Perceived usefulness of the website significantly affect the customer buying intention.	,000	Not Rejected.
H4b: Perceived risk of the website significantly affect the customer buying intention.	,620	Rejected.
H4c: Trust of the website significantly affect the customer buying intention.	,000	Not Rejected.

According to the hypotheses summarizes, the research model can be established as follows.

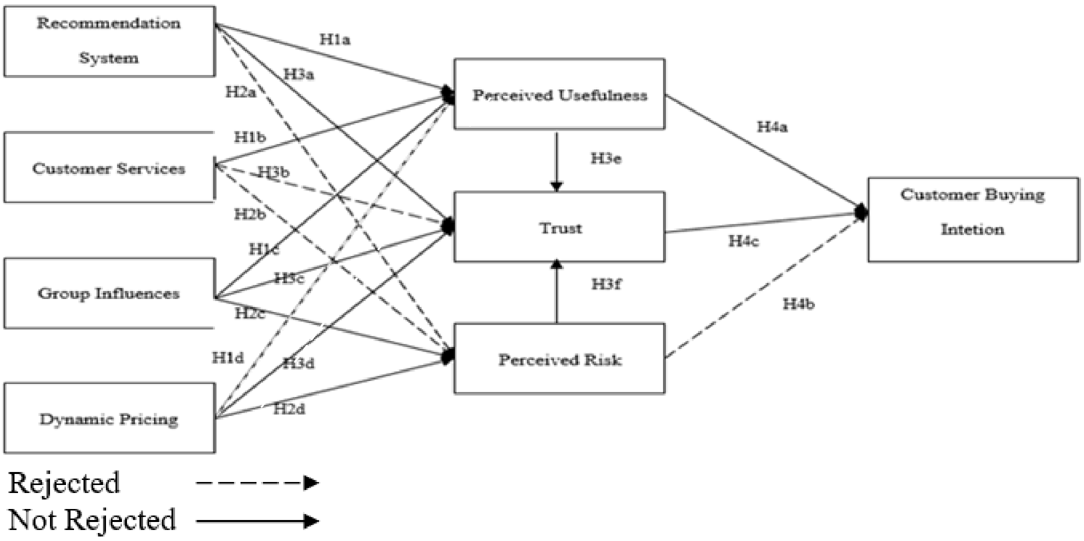

Figure 2: Model Summary

5.5. Differences of Customer Buying Intention, Trust, Perceived Usefulness and Perceived Risk According to Demographic Properties

Differences of PI, T, PU, PR according to demographic properties are shown at the flowing tables. All SPSS outputs are shown in Appendix C.

Table 31:Differences of customer buying intention, trust, perceived usefulness and perceived risk according to online shopping percentage

	Online	**N**	**Mean**	**Std.**	**F**	**p**	**Differences**
Customer Buying Intention	Below 10%[1]	73	15.233	6.383	46.394	**0.000**	**1<2** **1<3**
	10%-30%[2]	95	19.411	4.870			**1<4**
	30%-60%[3]	96	22.219	4.570			**2<3**
	60% and more[4]	72	24.403	4.168			**2<4** **3<4**
Trust	Below 10%[1]	73	13.397	3.231	33.785	**0.000**	**1<2** **1<3**
	10%-30%[2]	95	15.537	2.985			**1<4**
	30%-60%[3]	96	17.052	2.605			**2<3**
	60% and more[4]	72	17.597	2.372			**2<4**
Perceived Usefulness	Below 10%[1]	73	13.671	3.920	28.520	**0.000**	**1<2** **1<3** **1<4**
	10%-30%[2]	95	15.632	3.854			**2<3**
	30%-60%[3]	96	17.177	3.142			**2<4**
	60% and more[4]	72	18.708	2.880			**3<4**
Perceived Risk	Below 10%[1]	73	16.603	3.883	5.057	**0.002**	**3<2**
	10%-30%[2]	95	16.905	3.014			**4<2**
	30%-60%[3]	96	15.490	3.901			
	60% and more[4]	72	14.931	4.190			

Analysis results of the ANOVA test conducted to determine whether there is a difference in "Customer Buying Intention", "Trust", "Perceived Usefulness" and "Perceived Risk" variables according to the online shopping rates of the participants in the study are presented in Table 32. According to these findings, a statistically significant difference was found in the variables of "Customer Buying Intention", “Trust", "Perceived Usefulness" and "Perceived Risk" according to the online shopping rates of the participants ($p < 0.05$). As a result of the multiple comparison tests conducted to determine between which groups the difference is.

It was observed that the group "below 10%" (Average: 15.23 ± 6.38) in the variable of

"Customer Buying Intention" was lower than the other groups. It is observed that the "30-60%" group and the "60% and above" group are higher than the "10% -30%" group, while the "60% and over" group has the highest value. In other words, we can say that the customer buying intention of the more online shoppers is with positive training.

In the "Trust" variable, the "10% -30%" group (Mean: 15.53 ± 2.98), "30% -60%" group (Mean: 17.05 ± 2.60) and "60% and more The average of the participants in the "group" (Mean: 17.59 ± 2.37) is higher than the average of the participants in the "Below 10%" group (Average: 13.39 ± 3.23), in the "30% -60%" group (Average: 17 .05 ± 2.60) and the average of the participants in the "60% and more" group (Mean: 17.59 ± 2.37) than the average of the participants in the "10% -30%" group (Mean: 15.53 ± 2.98) is high. In other words, we can say that with the increase in online shopping as a percentage, the confidence in shopping has increased in direct proportion.

In the "Perceived Usefulness" variable, the "10% -30%" group (Mean: 15.63 ± 3.85), "30% -60%" group (Mean: 17.17 ± 3.14) and "60% and The average of the participants in the "more" group (Mean: 18.70 ± 2.87) is higher than the average of the participants in the "Below 10%" group (Average: 13.67 ± 3.91), in the "30% -60%" group (Mean: 17.17 ± 3.14) and the average of the participants in the "60% and more" group (Mean: 18.70 ± 2.87) compared to the average of the participants in the "10% -30%" group (Mean: 15.63 ± 3.85) the average of the participants in the "60% and more" group (Mean: 18.70 ± 2.87) is higher than the average of the participants in the "30% -60%" group (Mean: 17.17 ± 3.14). In other words, we can say that as the percentage of shopping increases, the perceived usefulness of the customers` increases.

In the "Perceived Risk" variable, the average of the participants in the "10% -30%" group (Mean: 16.90 ± 3.01) in the "30% -60%" group (Mean: 15.48 ± 3.90) and "60% and more" group (Mean: 14.93 ± 4.19) was determined to be higher than the average of the participants. So, we can see that the perceived risk decreases as the shopping percentage decreases.

Table 32: Differences of customer buying intention, trust, perceived usefulness and perceived risk according to gender

	Gender	**N**	**Mean**	**Std. Dev.**	**X^2**	**p**	**Differences**
Customer Buying Intention	Female[1]	195	20.3846154	6.31809455	1.688	0.429	-
	Male[2]	134	20.4925373	5.42861573			
	Not specified[3]	7	17.8571429	5.52052447			
Trust	Female[1]	195	16.1385	3.11404	3.211	0.201	-
	Male[2]	134	15.7463	3.32158			
	Not specified[3]	7	14.4286	3.15474			
Perceived Usefulness	Female[1]	195	16.1949	4.00811	6.512	**0.039**	**3<1**
	Male[2]	134	16.6642	3.61689			**3<2**
	Not specified[3]	7	12.5714	3.95209			
Perceived Risk	Female[1]	195	15.6923	3.80283	4.081	0.13	**-**
	Male[2]	134	16.5	3.7612			
	Not specified[3]	7	15.5714	4.15761			

The Anova analysis results, which were made to determine whether there is a difference in "Customer Buying Intention", "Trust", "Perceived Usefulness" and "Perceived Risk" variables according to the gender of the participants in the study, are presented in Table 33. According to these findings, a statistically significant difference was found in the "Perceived Usefulness" variable according to the gender of the participants ($p < 0.05$). As a result of the multiple comparisons, tests performed to determine between which groups the difference is, the average of the participants in the "Female" group (Mean: 16.19 ± 4.00) and in the "Male" group (Mean: 16.66 ± 3.61) It was determined that it was higher than the average of the participants in the "not specified" group (Mean: 12.57 ± 3.95). So, according to the table, we can say that perceived usefulness with male customers is more effective than female customers.

Table 33: Differences of customer buying intention, trust, perceived usefulness, and perceived risk according to age

	Age	N	Mean	Std. Dev.	F	p	Differences
Customer Buying Intention	18-24[1]	68	21.2703	5.4704	6.0783	**0.0001**	**1<2**
	25-34[2]	67	22.0306	4.6892			**3<2**
	35-44[3]	66	21.1970	6.3056			
	45-54[4]	37	18.7910	7.0120			
	55 and over[5]	98	18.2647	5.5169			
Trust	18-24[1]	37	15.4324	2.75419	3.735	**0.005**	**5<3**
	25-34[2]	98	16.1939	2.81622			
	35-44[3]	66	17.0606	3.17625			
	45-54[4]	67	15.5522	3.61513			
	55 and over[5]	68	15.1765	3.29605			
Perceived Usefulness	18-24[1]	37	16.6216	3.76646	3.992	**0.004**	**5<2**
	25-34[2]	98	16.8469	3.55038			**5<3**
	35-44[3]	66	17.3333	3.56622			
	45-54[4]	67	15.4328	4.71048			
	55 and over[5]	68	15.2206	3.47634			
Perceived Risk	18-24[1]	37	15.2162	3.66769	2.752	**0.028**	**2<3**
	25-34[2]	98	15.1735	3.85838			**2<4**
	35-44[3]	66	16.6667	3.6683			**2<5**
	45-54[4]	67	16.4478	3.97829			
	55 and over[5]	68	16.5882	3.5418			

Analysis results of the ANOVA test conducted to determine whether there is a difference in "Customer Buying Intention", "Trust", "Perceived Usefulness" and "Perceived Risk" variables according to the age of the participants in the study are presented in Table 34. According to these findings, a statistically significant difference was found in the variables of "Customer Buying Intention", "Trust", "Perceived Usefulness" and "Perceived Risk" according to the age of the participants ($p < 0.05$). As a result of the multiple comparison tests conducted to determine between which groups the difference is:

In the “Customer Buying Intention” variable, the average of the participants in the “25-34” group was found to be higher than the other groups. In other words, we can say that there is a significant relationship between the 25-34 age group and the desire to purchase on websites.

In the "Trust" variable, the average of the participants in the "35-44" group (Mean: 17.06 ± 3.17) was higher than the average of the participants in the "55 and over" group (Average: 15.17 ± 3.29). We can say that customers in the 35-44 age group are more effective in online shopping than other age groups.

In the "Perceived Usefulness" variable, the average of the participants in the "25-34" group (Average: 16.84 ± 3.55) and the "35-44" group (Mean: 17.33 ± 3.56) in the "55 and over" group (Average: 15.22 ± 3.47) higher than the average of the participants. We can say that perceived usefulness is more effective in 25-34 and 35-44 age groups compared to other age groups. So, it can be understood that these age groups find it more useful.

In the "Perceived Risk" variable, the "35-44" group (Mean: 16.66 ± 3.66), the "45-54" group (Average: 16.44 ± 3.97) and the "55 and over" group (Avg: 16.58 ± 3.54), it was determined that the average of the participants was higher than the average of the participants in the "25-34" group (Mean: 15.17 ± 3.85). We can understand that customers over the age of 35 see purchases made on online websites as riskier.

Table 34: Differences of customer buying intention, trust, perceived usefulness, and perceived risk according to monthly income

	Monthly Income	N	Mean	Std. Dev.	F	p	Differences
Customer Buying Intention	Below 2.000 TL[1]	30	21.0333	5.7923	0.3435	0.7939	-
	2001-6000 TL[2]	181	20.5359	5.7663			
	6001-10.000 TL[3]	76	19.9868	6.2875			
	10.000 TL and	49	19.9796	6.3459			
Trust	Below 2.000 TL[1]	30	15.6	3.0917	0.849	0.468	-
	2001-6000 TL[2]	181	15.9227	3.1806			
	6001-10.000 TL[3]	76	15.7368	3.29188			
	10.000 TL and	49	16.5714	3.22749			
Perceived Usefulness	Below 2.000 TL[1]	30	17.4333	3.75714	1.343	0.26	**-**
	2001-6000 TL[2]	181	16.337	3.70768			
	6001-10.000 TL[3]	76	15.7632	4.34778			
	10.000 TL and	49	16.3469	3.8327			
Perceived Risk	Below 2.000 TL[1]	30	16.6	3.89164	3.149	**0.025**	**2<3**
	2001-6000 TL[2]	181	15.5635	3.75242			**4<3**
	6001-10.000 TL[3]	76	17.0526	3.48289			
	10.000 TL and	49	15.6939	4.14932			

Analysis results of the ANOVA test conducted to determine whether there is a difference in "Customer Buying Intention", "Trust", "Perceived Usefulness" and "Perceived Risk" variables according to the monthly income of the participants in the study are presented in Table 35.

According to these findings, a statistically significant difference was found in the "Perceived Risk" variable according to the monthly income of the participants (p <0.05). As a result of the multiple comparison tests performed to determine which groups the difference is, the average of the participants in the "6001-10.000" group (Mean: 17.05 ± 3.48) in the "Perceived Risk" variable in the "2001-6000" group (Mean: 15.56 ± 3) , 75) and the "10.000 TL and above" group (Mean: 15.69 ± 4.14). In other words, we can understand that customers with 6k to 10k monthly income find online shopping riskier.

6. DISCUSSION OF THE FINDINGS

According to the findings, at least 12 remarkable points have been illuminated. In this section, each of these findings is discussed in terms of literature review.

Resnick (1997) stated that the recommendation system could provide consumers with a clue to perform other functions, such as evaluating product information and gaining knowledge of complementary or substitute products (Resnick & Varian, 1997). Research findings, according to H1a, showed that the recommendation system affected the usefulness of the website, meaning that they found the recommendation system by helping consumers in their shopping journey. In other words, the recommendation system serves as a utilitarian function by facilitating the shopping of consumers.

Many scientists thought seller prestige had a positive effect on online consumer confidence. Chrysanthos (2003) thought that prestige would be an important reference index in consumer selection with products of the same type (Dellarocas, 2003). According to Shardanand and Maes (1995), recommendations are often made based on a mix of past buying or browsing behaviour, characteristics of items being considered, and shoppers' demographic and personal preference information and trust (Shardanand & Maes, 1995). In this study, according to H1b, it was concluded that recommendation systems are perceived as safe by customers. In other words, consumers will be able to shop more securely on sites with a recommendation system.

According to Jian, Zhenhui Benbasat (2004), virtual reality or virtual product and customer service allow customers to interact with products online and explore a much wider range of these products, and previous research has shown that virtual reality improves consumers' brand attitudes, including improvement (Jian, Zhenhuı Benbasat, 2004). They stated that product knowledge and customer service are potential in terms of perceived benefit. Wang and Guan (2010) confirmed that the university library plays an important role in improving service quality through empirical analysis in three aspects of perceived benefit, service quality, information quality, and online system quality (Wang Y, 2010). According to the findings of the study, according to H1c, it has been understood that getting good customer service on websites increases the perceived usefulness of the service customers receive on their websites.

The groups they belong to emotionally affect consumers. Group effects were thought to cause a client to change their mindset with a review group. A study by Germany and Mirza (2013) suggested that online shoppers are affected by groups and a larger percentage of these groups are affected when making product purchasing decisions. Additionally, Germany and Mirza (2013) suggested that negative groups have a stronger negative effect than positive groups (Almana & Mirza, 2013). Our research has enabled us to determine whether data, comments and evaluations provided by groups or individuals who have previously transacted on websites affect the useof customers' websites or product offerings or services and whether sites are at risk. Consumers post their feedback after purchasing a product or service on the website. According to Ahmad et al. (2014) feedback is not considered fake online marketing and has been suggested to be untrusted (Ahmad et al., 2014). In this sense, according to H2c, it was understood in the study that the group effect affects the consumer in terms of trust in the site.

Dynamic pricing, often referred to financially as individual price discrimination, has become more common with the spread of Internet Marketing. Kotler et al. (2010), dynamic pricing is accepted as an individual level price differentiation strategy where prices are applied according to the customer, location, product, or time (Kotler, P., Kartajaya, H., & Setiawan, 2010). According to Garbarino and Lee (2003), dynamic pricing can be of interest to most sellers, with the ability to use newly available information to individually adjust prices based on a particular customer's payment request (Garbarino & Lee, 2003). In addition, according to Erevelles (2016), it has been argued that dynamic pricing practices in responses to segment and individual-level differences by sellers affect online customers' behaviour and perceived situations (Erevelles et al., 2016). According to this research, H2d and H3d hypotheses, it has been seen that most customers have a benefit and dynamic pricing effect from websites, that is, the dynamic pricing application on websites has been perceived as beneficial by customers, and it has been found that shopping through the sites is risk-free and the site trust is increased.

Perceived usefulness means that online buyers think that using this system individually can improve their business performance. There are many areas currently investigating the impact of perceived usefulness. In the introduction of technology, Snchez and Hueros (2010) found that perceived usefulness can affect the user purchasing approach and user behaviour has an impact on new technologies (Sánchez & Duarte-Hueros, 2010). Koufaris and Hampton (2002) explained the impact of environmental psychology on the consumer in the field of online shopping. Koufaris and Hampton (2002) considered that perceived enjoyment would have a positive impact on trust by perceived usefulness and perceived ease of use when consumers shop online through the website (Koufaris & Hampton-Sosa, 2002). They thought that perceived usefulness had a more significant effect on online shopping consumer behaviour than other factors. From previous people's research, we can find that the main determinant is perceived as the benefit of consumers regardless of whether they are willing to adopt new information systems or technology. For this reason, it has been understood, according to H3e and H4a hypotheses, that the perceived usefulness affects the trust in websites and influences the buying intention and behaviour of the customer.

The effect of perceived risk on trust is also suggested by academics. It is thought that the perceived risk in the online shopping environment negatively affects trust (Kimery & McCord, 2002). Heijden (2003) thought that reducing perceived risk could indeed increase the confidence of online shopping and thus increase the online shopping intentions of buyers. According to the results obtained in this study, it was seen that the perceived shopping risk on websites influenced trust. In other words, if the consumer does not perceive any risky situation while shopping on the website, trusts the site. The group influence, reminder system and the risks not perceived from the sites also make the customers trust the sites and show that they are directly related to their purchase intentions. In other words, according to H3a, H3c, H3e,H3f and H4c, we can say that customers who trust the sites have a purchase intention.

Perceived usefulness is the subjective assessment that new technology can benefit users from their psychological level. Logically speaking, this is only when people feel that technology can help their business and they will use technology in their lives. According to Davis (1989), the perceived utility can affect consumer behaviour (Davis, 1989). Yang et al. (2006) additionally confirmed the presence of this effect (Yang et al., 2006). According to the results of this research, it has been observed that the perceived usefulness during shopping influences the buying intention of the consumer. In other words, the consumer prefers to shop on useful and shop from trustful sites.

Wang and Emurian (2005) thought that shopping on websites and their future development would be vulnerable due to the lack of an atmosphere of trust (Wang &

Emurian, 2005). Gefen et al. (2003) showed that consumer familiarity and trust in the website and its process has a significant positive impact on consumer purchasing behaviour (Gefen et al., 2003). Research by Heijden (2003) showed the same result (van der Heijden et al., 2003). Trust will determine the consumer's purchase intention by influencing the consumer's attitude. By reviewing 45 research articles in academic journals, Chang et al. (2005) found that lack of trust is a major obstacle to online shopping (Chang & Wu, 2005). As the research was conducted in the context of big data, he found that the factor of trust is necessary as an important factor influencing the buying intention of the consumer.

7. CONCLUSION

In the age of big data, shopping sites can find consumer demand preferences and points by tracking changes in consumer demand through various channels in real-time so that each consumer can experience "one-to-one" personalized shopping services at the maximum level. To offer products that meet the needs of consumers to meet the prices, features, quantity, size, brand, style, and other features of the recommended products in the best way.

It is the selection criteria and the preferences of the consumers that will increase the acceptance and satisfaction of the consumer goods recommendation system. (H, 2013) The study seeks to address several implications that can help develop marketing strategies for online marketing in the big data age. The recommendation system increases the intentions and behaviours of the customers by easily increasing the self-preferences and interest of the consumers. Moreover, from the customer's point of view, it enables customers to make the decision when buying whether they want to buy from the suggestion system to improve, so the products are more welcomed to their preferences. Furthermore, products recommended by a system are more reliable, which leads to more gains in trust, pleasure, and a sense of motivation. With the development of knowledge in technology and online marketing, the problem of information overload and selection complexity is getting more orderly. Therefore, e-sellers should improve the search for matching result information to lower their cognitive cost. Dynamic pricing and improved customer service are practices that need to be noticed to make customers more satisfied.

The purpose of the study works in variables combined conditions in Turkey in the big data infrastructure to users with the variables (CS, RS, GI etc.) customer buying intention 'to find an impact and develop a model.

For this purpose, an anonymous survey was conducted to 336 people online and the results of the survey were analyzed in detail through the SPSS program.

According to the regression analysis, 17 hypotheses were tested, and 5 hypotheses could not be supported by the results of the survey. It has been observed that trust, perceived usefulness, group influences, customer services, dynamic pricing and recommendation systems are effective on sites that use big data infrastructure to examine customer buying intention. However, the impact of perceived risk on purchase intention was not supported. According to demographic variables, online shopping percentage and age group vary significantly for trust, customer buying intention, perceived usefulness, and risk. However, it is not possible to say this result for its relationship with other demographic variables.

Consequently, we model using a combination of big data infrastructure conditions in Turkey has laid down an important model for a new site.

8. LIMITATIONS AND FUTURE RESEARCH

The sample of this study is limited to potential customers, so future studies are diverse demographic populations. Also, the sample participants are from Turkey and there may be a limitation for the study. However, the contribution of this study is valuable and developing countries such as Turkey. A cross-cultural comparison can be made between subsequent studies.

The current study used user feedback of their responses as the dependent variable. Users' feedback is often used as a proxy measure for behavior, while the actual purchase situation has been accurately predicted. Therefore, the results found in this study have been carefully understood and applied. Similar studies in the future should be measured to fit the actual online environment.

Online analysis is recommended for future research. Explore other implications of implementing Big Data analytics and can be caught in instant changes in customers' responses.

This research can contribute to similar product-based and sector-based future studies. However, systems that can watch the process live and have a larger data size will be able to give a more permanent result.

For each variable considered in the study, sector, age, region, etc. It is recommended to work with variables smaller or larger data sets. To give an example, researching the effect of dynamic pricing, guess, reminder system, customer services on products basis, researching regional effects, age group, gender or specific time interval, etc. It is also recommended to conduct studies on the basis of the variables used in the research. It is expected that this research will contribute to similar studies.

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APPENDIX A:
Online Questionnaire

Online Alışveriş Deneyimi Anketi

Merhaba,
Yeditepe Universitesi MBA`e bagli akademik tez calismasi yapiyorum. Anketin literature katkisi, big data alt yapisini kullanan online alisveris sitelerinin musterilerine potansiyel pozitif ve negatif etkileri incelenecektir.
Destekleriniz icin simdiden tesekkur ederim.
Ibrahim Gokhan ZENGIN

*Required

1. En son alisveris yaptiginiz site *

____

2. Web sitesi uzerinden en son ne almistiniz ? *

Mark only one oval.

- ◯ Giyim
- ◯ Elektronik
- ◯ Kitap, film, muzik, oyun
- ◯ Kozmetik, kisisel bakim
- ◯ Canta veya aksesuar
- ◯ Gida
- ◯ Ev Aletleri
- ◯ Mobilya veya Ev Esyalari
- ◯ Oyuncak veya Bebek urunleri

Lütfen aşağıdaki soruları alışveriş yaptığınız web sitelerine göre cevaplayınız..

3. Alışverişimi web siteleri uzerinden yapmak isterim. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	◯	◯	◯	◯	◯	◯	◯	Kesinlikle katiliyorum.

4. Alışverişimi web sitelerinden yapmaya devam edeceğim. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	◯	◯	◯	◯	◯	◯	◯	Kesinlikle katiliyorum.

5. Web sitelerinden satin almak icin harekete gecerim. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	◯	◯	◯	◯	◯	◯	◯	Kesinlikle katiliyorum.

6. Web sitesinden yaptigim alisverisi. arkadaslarima ve aileme tavsiye ederim. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	◯	◯	◯	◯	◯	◯	◯	Kesinlikle katiliyorum.

Lütfen aşağıdaki soruları online alışveriş siteleri için cevaplayınız..

7. Online alışveriş siteleri satın almak istediğim ürün için ikame (yerine gecen) ürünler önerebilir. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Kesinlikle katiliyorum.

8. Online alışveriş siteleri. satın almak istediğim ürün için tamamlayıcı ürünler önerebilir. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Kesinlikle katiliyorum.

9. Online alışveriş siteleri benim beğenebileceğim ya da sitenin en çok satan ürünlerini önerebilir. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Kesinlikle katiliyorum.

10. Online alışveriş siteleri tarafından sunulan tavsiye bilgilerinin bir nezaket göstergesi olduğuna inanıyorum. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Kesinlikle katiliyorum.

11. Online alışveriş siteleri müşterileri desteklemek için bir kanal (iletişim no.email vb.) sunmaktadır. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Kesinlikle katiliyorum.

12. Online alışverişte siparişimi takip edebilmeyi beklerim. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Kesinlikle katiliyorum.

13. Sanal deneyim sağlayan alışveriş sitesi. daha uygun ürünler seçmemi sağlayabilir. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Kesinlikle katiliyorum.

14. Ürünleri satın almış müşterilerin yorumlarina başvurabilirim. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Kesinlikle katiliyorum.

15. İnternetten bir ürün satın almak istediğimde. web sitesinde sunulan değerlendirmeler karar vermemde yardımcı oluyor. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	◯	◯	◯	◯	◯	◯	◯	Kesinlikle katiliyorum.

16. Web sitesinde yayınlanan yorumlar satın alma kararımı etkiler. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	◯	◯	◯	◯	◯	◯	◯	Kesinlikle katiliyorum.

17. Başkalarının diğer ürün yorumlarının ne kadar işe yaradığını değerlendirmesi. satın alma kararımı etkiler. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	◯	◯	◯	◯	◯	◯	◯	Kesinlikle katiliyorum.

18. Yorumlari/Incelemeleri sunan web sitesinin popülerliği satın alma kararımı etkiler. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	◯	◯	◯	◯	◯	◯	◯	Kesinlikle katiliyorum.

19. Alışveriş web sitelerinin çerezler aracılığıyla kişisel bilgi topladığını biliyorum. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	◯	◯	◯	◯	◯	◯	◯	Kesinlikle katiliyorum.

20. Alışveriş sitelerinin kişiselleştirilmiş ürün önerileri ve reklamlar için toplanan bilgileri kullandığını biliyorum. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	◯	◯	◯	◯	◯	◯	◯	Kesinlikle katiliyorum.

21. Alışveriş web sitelerinin toplanan bilgileri ürünlerin fiyatında değişiklik yapmak için kullandığını biliyorum. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	◯	◯	◯	◯	◯	◯	◯	Kesinlikle katiliyorum.

22. Alışveriş web sitesindeki sorunlara dair değerlendirmeler gördüğümde, siteden hicbirsey satin almam. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	◯	◯	◯	◯	◯	◯	◯	Kesinlikle katiliyorum.

23. Web sitesi uzerinden alisverisi düşük riskli olduğunu düşündüğüm için tercih ederim. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	◯	◯	◯	◯	◯	◯	◯	Kesinlikle katiliyorum.

24. Online alışveriş yaparken hesap bilgilerimin virus veya hackerlar tarafindan calinmasindan endiseleniyorum. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	◯	◯	◯	◯	◯	◯	◯	Kesinlikle katiliyorum.

25. Online alisveris yaparken. riski hissediyorum. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	◯	◯	◯	◯	◯	◯	◯	Kesinlikle katiliyorum.

26. Online alışveriş ile zamandan ve paradan tasarruf edilebilir. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	◯	◯	◯	◯	◯	◯	◯	Kesinlikle katiliyorum.

27. Web sitesi uzerinden alisverisi kullandığımda eğlenebilir ve zamanımın tadını çıkaririm. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.								Kesinlikle katiliyorum.

28. Tek kelimeyle. online alışveriş benim için çok yararlı. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.								Kesinlikle katiliyorum.

29. Web sitelerinden alışverişin güvenilir olduğunu düşünüyorum. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.								Kesinlikle katiliyorum.

30. Web sitelerinin bilinir ve güvenilir tedarikçilerle çalışması. tüketiciler tarafından benimsenmesini etkileyecektir. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.								Kesinlikle katiliyorum.

31. Web sitelerinden alışveriş yaptığımda rahatim. *

Mark only one oval.

	1	2	3	4	5	6	7	
Kesinlikle katilmiyorum.	◯	◯	◯	◯	◯	◯	◯	Kesinlikle katiliyorum.

32. Cinsiyet *

Mark only one oval.

◯ Erkek
◯ Kadin
◯ Belirtmemeyi tercih ediyorum.

33. Yas Araligi *

Mark only one oval.

◯ 18-24
◯ 25-34
◯ 35-44
◯ 45-54
◯ 55 ve ustu

34. Medeni Haliniz *

Mark only one oval.

◯ Bekar (Hic evlenmedim.)
◯ Evli
◯ Bosanmis
◯ Dul

35. Tamamladığınız en yüksek okul derecesi veya seviyesi nedir? *

Mark only one oval.

- Ilkokul
- Lise
- Universite
- Yuksek Lisans (Master)
- Doktora
- Diger

36. Aylik Geliriniz *

Mark only one oval.

- 2000 TL Alti
- 2001-6000TL Arasinda
- 6001-10000 TL Arasinda
- 10001 TL Ustu

37. Internet uzerinden genellikle ne satin alirsiniz? *

Mark only one oval.

- Kitap
- Elektronik (Laptop, Telefon vb)
- Kozmetik veya Kisisel Bakim
- Oyun veya Oyun Konsolu
- El Aletleri veya Donanim (Ev, Mutfak, Bahce vb)
- Evcil Hayvan Aksesuarlari
- Giyim
- Spor Ekipmanlari
- Gida
- Diger

38. Alisverislerimin yuzde kacini online yaparim ? *

Mark only one oval.

- %10 ve altinda
- %11-%30 arasinda
- %31-%60 arasinda
- %61-%80 arasinda
- %81 ve ustunu

APPENDIX B:
RELIABILITY ANALYSIS OUTPUTS

Table B1: Reliability Analysis for Purchase Intention

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PI1	15.37	20.533	.856	.915
PI2	15.23	20.428	.879	.907
PI3	15.43	19.487	.853	.916
PI4	15.10	21.125	.811	.929

Table B2: Reliability Analysis for Group Influences

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
GI1	17.90	12.205	.694	.843
GI2	17.87	11.899	.814	.795
GI3	17.91	12.330	.778	.810
GI4	18.01	12.901	.611	.877

Table B3: Reliability Analysis for Customer Services

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
CS1	18.40	9.917	.422	.715
CS2	16.93	11.496	.533	.642
CS3	17.74	9.660	.570	.606
CS4	17.23	10.929	.519	.642

Table B4 : Reliability Analysis for Recommendation System

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
RS1	14.67	18.382	.643	.685
RS2	14.30	18.891	.686	.664
RS3	13.99	20.997	.642	.696
RS4	15.06	21.770	.386	.825

Table B5 : Reliability Analysis for Perceived Risk

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PR1	15.50	11.469	.227	.344
PR2	16.01	14.460	-.051	.607
PR3	15.24	9.895	.383	.171
PR4	15.71	9.306	.417	.121

Table B6 : Reliability Analysis for Perceived Risk

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PU1	10.40	8.384	.632	.740
PU2	11.11	6.465	.677	.686
PU3	11.10	7.375	.628	.735

Table B7 : Reliability Analysis for Trust

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
T1	11.25	4.234	.597	.398
T2	9.73	7.710	.228	.828
T3	10.92	4.008	.677	.266

Table B8 : Reliability Analysis for Dynamic Pricing

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
DP1	11.23	6.971	.681	.573	.669
DP2	11.05	7.699	.731	.597	.640
DP3	11.90	7.146	.528	.285	.852

APPENDIX C

SPSS Outputs for Differences of Customer Buying Intention, Trust, Perceived Usefulness and Perceived Risk According to Demographic Properties

Descriptive

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minim m
Trust	Below 10%	73	13,3973	3,23067	,37812	12,6435	14,1510	6,0
	10%-30%	95	15,5368	2,98511	,30627	14,9287	16,1449	8,0
	30%-60%	96	17,0521	2,60514	,26589	16,5242	17,5799	11,0
	60% and more	72	17,5972	2,37154	,27949	17,0399	18,1545	11,0
	Total	336	15,9464	3,20309	,17474	15,6027	16,2902	6,0
Perceived Usefulness	Below 10%	73	13,6712	3,91952	,45875	12,7567	14,5857	4,0
	10%-30%	95	15,6316	3,85385	,39540	14,8465	16,4166	7,0
	30%-60%	96	17,1771	3,14222	,32070	16,5404	17,8138	9,0
	60% and more	72	18,7083	2,87993	,33940	18,0316	19,3851	11,0
	Total	336	16,3065	3,88930	,21218	15,8892	16,7239	4,0
Perceived Risk	Below 10%	73	16,6027	3,88280	,45445	15,6968	17,5087	7,0
	10%-30%	95	16,9053	3,01441	,30927	16,2912	17,5193	8,0
	30%-60%	96	15,4896	3,90140	,39819	14,6991	16,2801	6,0
	60% and more	72	14,9306	4,19029	,49383	13,9459	15,9152	6,0
	Total	336	16,0119	3,80257	,20745	15,6038	16,4200	6,0

Test of Homogeneity of Variances

		Levene Statistic	df1	df2	S
Trust	Based on Mean	2,850	3	332	
	Based on Median	2,675	3	332	
	Based on Median and with adjusted df	2,675	3	317,660	
	Based on trimmed mean	2,883	3	332	
Perceived Usefulness	Based on Mean	4,635	3	332	
	Based on Median	4,426	3	332	
	Based on Median and with adjusted df	4,426	3	327,176	
	Based on trimmed mean	4,865	3	332	
Perceived Risk	Based on Mean	4,215	3	332	
	Based on Median	3,913	3	332	
	Based on Median and with adjusted df	3,913	3	316,705	
	Based on trimmed mean	4,081	3	332	

ANOVA

		Sum of Squares	df	Mean Square	F	S
Trust	Between Groups	803,876	3	267,959	33,785	
	Within Groups	2633,160	332	7,931		
	Total	3437,036	335			
Perceived Usefulness	Between Groups	1038,346	3	346,115	28,520	
	Within Groups	4029,079	332	12,136		
	Total	5067,426	335			
Perceived Risk	Between Groups	211,683	3	70,561	5,057	
	Within Groups	4632,269	332	13,953		
	Total	4843,952	335			

Multiple Comparisons

Dependent Variable		(I) Online_shopping_percentage_4Groups	(J) Online_shopping_percentage_4Groups	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Trust	Tukey HSD	Below 10%	10%-30%	-2,13958*	,43833	,000	-3,2714	-1,0078
			30%-60%	-3,65482*	,43734	,000	-4,7841	-2,5256
			60% and more	-4,19996*	,46776	,000	-5,4078	-2,9922
		10%-30%	Below 10%	2,13958*	,43833	,000	1,0078	3,2714
			30%-60%	-1,51524*	,40756	,001	-2,5676	-,4629
			60% and more	-2,06038*	,44005	,000	-3,1966	-,9241
		30%-60%	Below 10%	3,65482*	,43734	,000	2,5256	4,7841
			10%-30%	1,51524*	,40756	,001	,4629	2,5676
			60% and more	-,54514	,43906	,601	-1,6788	,5885
		60% and more	Below 10%	4,19996*	,46776	,000	2,9922	5,4078
			10%-30%	2,06038*	,44005	,000	,9241	3,1966
			30%-60%	,54514	,43906	,601	-,5885	1,6788
	LSD	Below 10%	10%-30%	-2,13958*	,43833	,000	-3,0018	-1,2773

Trust

	Online_shopping_percentage_4Groups	N	Subset for alpha = 0.05		
			1	2	3
Tukey HSD[a,b]	Below 10%	73	13,3973		
	10%-30%	95		15,5368	
	30%-60%	96			17,0521
	60% and more	72			17,5972
	Sig.		1,000	1,000	,600

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 82.422.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Perceived_Usefulness

	Online_shopping_percentage_4Groups	N	Subset for alpha = 0.05			
			1	2	3	4
Tukey HSD[a,b]	Below 10%	73	13,6712			
	10%-30%	95		15,6316		
	30%-60%	96			17,1771	
	60% and more	72				18,7083
	Sig.		1,000	1,000	1,000	1,000

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 82.422.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Perceived_Risk

	Online_shopping_percentage_4Groups	N	Subset for alpha = 0.05 1	2
Tukey HSD[a,b]	60% and more	72	14,9306	
	30%-60%	96	15,4896	15,4896
	Below 10%	73		16,6027
	10%-30%	95		16,9053
	Sig.		,772	,073

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 82.422.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
Trust	Female	195	16,1385	3,11404	,22300	15,6986	16,5783	7,00	21,00
	Male	134	15,7463	3,32158	,28694	15,1787	16,3138	6,00	21,00
	Not specified	7	14,4286	3,15474	1,19238	11,5109	17,3462	12,00	21,00
	Total	336	15,9464	3,20309	,17474	15,6027	16,2902	6,00	21,00
Perceived_Usefulness	Female	195	16,1949	4,00811	,28703	15,6288	16,7610	4,00	21,00
	Male	134	16,6642	3,61689	,31245	16,0462	17,2822	8,00	21,00
	Not specified	7	12,5714	3,95209	1,49375	8,9164	16,2265	9,00	21,00
	Total	336	16,3065	3,88930	,21218	15,8892	16,7239	4,00	21,00
Perceived_Risk	Female	195	15,6923	3,80283	,27233	15,1552	16,2294	6,00	21,00
	Male	134	16,5000	3,76120	,32492	15,8573	17,1427	7,00	21,00
	Not specified	7	15,5714	4,15761	1,57143	11,7263	19,4166	9,00	21,00
	Total	336	16,0119	3,80257	,20745	15,6038	16,4200	6,00	21,00

Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Trust	Based on Mean	1,091	2	333	,337
	Based on Median	1,519	2	333	,220
	Based on Median and with adjusted df	1,519	2	321,741	,220
	Based on trimmed mean	1,009	2	333	,366
Perceived_Usefulness	Based on Mean	1,398	2	333	,249
	Based on Median	1,280	2	333	,279
	Based on Median and with adjusted df	1,280	2	321,938	,279
	Based on trimmed mean	1,496	2	333	,225
Perceived_Risk	Based on Mean	,123	2	333	,884
	Based on Median	,124	2	333	,883
	Based on Median and with adjusted df	,124	2	330,246	,883
	Based on trimmed mean	,146	2	333	,864

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Trust	Between Groups	28,687	2	14,343	1,401	,248
	Within Groups	3408,349	333	10,235		
	Total	3437,036	335			
Perceived_Usefulness	Between Groups	117,228	2	58,614	3,943	,020
	Within Groups	4950,197	333	14,865		
	Total	5067,426	335			
Perceived_Risk	Between Groups	53,200	2	26,600	1,849	,159
	Within Groups	4790,753	333	14,387		
	Total	4843,952	335			

Trust

	Gender	N	Subset for alpha = 0.05
			1
Tukey HSD[a,b]	Not specified	7	14,4286
	Male	134	15,7463
	Female	195	16,1385
	Sig.		,222

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 19.299.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Perceived_Usefulness

	Gender	N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a,b]	Not specified	7	12,5714	
	Female	195		16,1949
	Male	134		16,6642
	Sig.		1,000	,924

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 19.299.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Perceived_Risk

	Gender	N	Subset for alpha = 0.05
			1
Tukey HSD[a,b]	Not specified	7	15,5714
	Female	195	15,6923
	Male	134	16,5000
	Sig.		,727

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 19.299.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Ranks

	Gender	N	Mean Rank
Trust	Female	195	173,72
	Male	134	163,81
	Not specified	7	112,79
	Total	336	
Perceived_Usefulness	Female	195	166,63
	Male	134	175,76
	Not specified	7	81,50
	Total	336	
Perceived_Risk	Female	195	159,91
	Male	134	181,58
	Not specified	7	157,50
	Total	336	

Test Statistics[a,b]

	Trust	Perceived_Usefulness	Perceived_Risk
Kruskal-Wallis H	3,211	6,512	4,081
df	2	2	2
Asymp. Sig.	,201	,039	,130

a. Kruskal Wallis Test

b. Grouping Variable: Gender

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
Trust	18-24	37	15,4324	2,75419	,45279	14,5141	16,3507	9,00	20,00
	25-34	98	16,1939	2,81622	,28448	15,6293	16,7585	8,00	21,00
	35-44	66	17,0606	3,17625	,39097	16,2798	17,8414	6,00	21,00
	45-54	67	15,5522	3,61513	,44166	14,6704	16,4340	7,00	21,00
	55 and over	68	15,1765	3,29605	,39970	14,3787	15,9743	9,00	21,00
	Total	336	15,9464	3,20309	,17474	15,6027	16,2902	6,00	21,00
Perceived_Usefulness	18-24	37	16,6216	3,76646	,61920	15,3658	17,8774	9,00	21,00
	25-34	98	16,8469	3,55038	,35864	16,1351	17,5587	8,00	21,00
	35-44	66	17,3333	3,56622	,43897	16,4566	18,2100	10,00	21,00
	45-54	67	15,4328	4,71048	,57548	14,2839	16,5818	4,00	21,00
	55 and over	68	15,2206	3,47634	,42157	14,3791	16,0620	8,00	21,00
	Total	336	16,3065	3,88930	,21218	15,8892	16,7239	4,00	21,00
Perceived_Risk	18-24	37	15,2162	3,66769	,60296	13,9933	16,4391	8,00	21,00
	25-34	98	15,1735	3,85838	,38976	14,3999	15,9470	6,00	21,00
	35-44	66	16,6667	3,66830	,45154	15,7649	17,5684	8,00	21,00
	45-54	67	16,4478	3,97829	,48603	15,4774	17,4181	8,00	21,00
	55 and over	68	16,5882	3,54180	,42951	15,7309	17,4455	7,00	21,00

Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Trust	Based on Mean	2,569	4	331	,038
	Based on Median	2,330	4	331	,056
	Based on Median and with adjusted df	2,330	4	320,117	,056
	Based on trimmed mean	2,558	4	331	,039
Perceived_Usefulness	Based on Mean	3,523	4	331	,008
	Based on Median	2,199	4	331	,069
	Based on Median and with adjusted df	2,199	4	296,948	,069
	Based on trimmed mean	3,267	4	331	,012
Perceived_Risk	Based on Mean	,425	4	331	,791
	Based on Median	,265	4	331	,900
	Based on Median and with adjusted df	,265	4	317,412	,900
	Based on trimmed mean	,415	4	331	,798

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Trust	Between Groups	148,431	4	37,108	3,735	,005
	Within Groups	3288,605	331	9,935		
	Total	3437,036	335			
Perceived_Usefulness	Between Groups	233,213	4	58,303	3,992	,004
	Within Groups	4834,212	331	14,605		
	Total	5067,426	335			
Perceived_Risk	Between Groups	155,927	4	38,982	2,752	,028
	Within Groups	4688,026	331	14,163		
	Total	4843,952	335			

Multiple Comparisons

Dependent Variable		(I) Age	(J) Age	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Trust	Tukey HSD	18-24	25-34	-,76145	,60820	,721	-2,4297	,9068
			35-44	-1,62817	,64735	,090	-3,4038	,1474
			45-54	-,11981	,64561	1,000	-1,8906	1,6510
			55 and over	,25596	,64392	,995	-1,5102	2,0222
		25-34	18-24	,76145	,60820	,721	-,9068	2,4297
			35-44	-,86673	,50191	,419	-2,2434	,5100
			45-54	,64164	,49967	,701	-,7289	2,0122
			55 and over	1,01741	,49748	,247	-,3471	2,3819
		35-44	18-24	1,62817	,64735	,090	-,1474	3,4038
			25-34	,86673	,50191	,419	-,5100	2,2434
			45-54	1,50837*	,54665	,048	,0090	3,0078
			55 and over	1,88414*	,54465	,006	,3902	3,3780
		45-54	18-24	,11981	,64561	1,000	-1,6510	1,8906
			25-34	-,64164	,49967	,701	-2,0122	,7289
			35-44	-1,50837*	,54665	,048	-3,0078	-,0090
			55 and over	,37577	,54258	,958	-1,1125	1,8640
		55 and over	18-24	-,25596	,64392	,995	-2,0222	1,5102
			25-34	-1,01741	,49748	,247	-2,3819	,3471
			35-44	-1,88414*	,54465	,006	-3,3780	-,3902
			45-54	-,37577	,54258	,958	-1,8640	1,1125
	LSD	18-24	25-34	-,76145	,60820	,211	-1,9579	,4350
			35-44	-1,62817*	,64735	,012	-2,9016	-,3547
			45-54	-,11981	,64561	,853	-1,3898	1,1502
			55 and over	,25596	,64392	,691	-1,0107	1,5227
		25-34	18-24	,76145	,60820	,211	-,4350	1,9579
			35-44	-,86673	,50191	,085	-1,8541	,1206
			45-54	,64164	,49967	,200	-,3413	1,6246
			55 and over	1,01741*	,49748	,042	,0388	1,9960
		35-44	18-24	1,62817*	,64735	,012	,3547	2,9016
			25-34	,86673	,50191	,085	-,1206	1,8541
			45-54	1,50837*	,54665	,006	,4330	2,5837

Trust

	Age	N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a,b]	55 and over	68	15,1765	
	18-24	37	15,4324	
	45-54	67	15,5522	15,5522
	25-34	98	16,1939	16,1939
	35-44	66		17,0606
	Sig.		,386	,065

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 60.965.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Perceived_Usefulness

	Age	N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a,b]	55 and over	68	15,2206	
	45-54	67	15,4328	
	18-24	37	16,6216	16,6216
	25-34	98	16,8469	16,8469
	35-44	66		17,3333
	Sig.		,132	,842

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 60.965.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Perceived_Risk

	Age	N	Subset for alpha = 0.05
			1
Tukey HSD[a,b]	25-34	98	15,1735
	18-24	37	15,2162
	45-54	67	16,4478
	55 and over	68	16,5882
	35-44	66	16,6667
	Sig.		,186

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 60.965.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Ranks

	Age	N	Mean Rank
Trust	18-24	37	150,14
	25-34	98	174,92
	35-44	66	202,84
	45-54	67	159,54
	55 and over	68	144,74
	Total	336	
Perceived_Usefulness	18-24	37	175,41
	25-34	98	180,19
	35-44	66	194,68
	45-54	67	153,94
	55 and over	68	136,82
	Total	336	
Perceived_Risk	18-24	37	145,45
	25-34	98	147,04
	35-44	66	185,55
	45-54	67	182,84
	55 and over	68	181,29
	Total	336	

Test Statistics[a,b]

	Trust	Perceived_Usefulness	Perceived_Risk
Kruskal-Wallis H	14,786	15,316	11,643
df	4	4	4
Asymp. Sig.	,005	,004	,020

a. Kruskal Wallis Test

b. Grouping Variable: Age

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
Trust	Below 2.000 TL	30	15,6000	3,09170	,56446	14,4455	16,7545	10,00	21,00
	2001-6000 TL	181	15,9227	3,18060	,23641	15,4562	16,3891	6,00	21,00
	6001-10.000 TL	76	15,7368	3,29188	,37760	14,9846	16,4891	9,00	21,00
	10.000 TL and above	49	16,5714	3,22749	,46107	15,6444	17,4985	9,00	21,00
	Total	336	15,9464	3,20309	,17474	15,6027	16,2902	6,00	21,00
Perceived_Usefulness	Below 2.000 TL	30	17,4333	3,75714	,68596	16,0304	18,8363	9,00	21,00
	2001-6000 TL	181	16,3370	3,70768	,27559	15,7932	16,8808	4,00	21,00
	6001-10.000 TL	76	15,7632	4,34778	,49872	14,7696	16,7567	7,00	21,00
	10.000 TL and above	49	16,3469	3,83270	,54753	15,2461	17,4478	8,00	21,00
	Total	336	16,3065	3,88930	,21218	15,8892	16,7239	4,00	21,00
Perceived_Risk	Below 2.000 TL	30	16,6000	3,89164	,71051	15,1468	18,0532	8,00	21,00
	2001-6000 TL	181	15,5635	3,75242	,27892	15,0132	16,1139	6,00	21,00

Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Trust	Based on Mean	,579	3	332	,629
	Based on Median	,521	3	332	,668
	Based on Median and with adjusted df	,521	3	330,808	,668
	Based on trimmed mean	,564	3	332	,639
Perceived_Usefulness	Based on Mean	2,084	3	332	,102
	Based on Median	1,379	3	332	,249
	Based on Median and with adjusted df	1,379	3	324,719	,249
	Based on trimmed mean	1,956	3	332	,120
Perceived_Risk	Based on Mean	,324	3	332	,808
	Based on Median	,186	3	332	,906
	Based on Median and with adjusted df	,186	3	317,698	,906
	Based on trimmed mean	,267	3	332	,849

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Trust	Between Groups	26,182	3	8,727	,849	,468
	Within Groups	3410,854	332	10,274		
	Total	3437,036	335			
Perceived_Usefulness	Between Groups	60,778	3	20,259	1,343	,260
	Within Groups	5006,648	332	15,080		
	Total	5067,426	335			
Perceived_Risk	Between Groups	134,035	3	44,678	3,149	,025
	Within Groups	4709,917	332	14,186		
	Total	4843,952	335			

Multiple Comparisons

Dependent Variable		(I) Monthly_income	(J) Monthly_income	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Trust	Tukey HSD	Below 2.000 TL	2001-6000 TL	-,32265	,63184	,957	-1,9541	1,3088
			6001-10.000 TL	-,13684	,69111	,997	-1,9214	1,6477
			10.000 TL and above	-,97143	,74305	,559	-2,8900	,9472
		2001-6000 TL	Below 2.000 TL	,32265	,63184	,957	-1,3088	1,9541
			6001-10.000 TL	,18581	,43811	,974	-,9454	1,3170
			10.000 TL and above	-,64878	,51617	,591	-1,9816	,6840
		6001-10.000 TL	Below 2.000 TL	,13684	,69111	,997	-1,6477	1,9214
			2001-6000 TL	-,18581	,43811	,974	-1,3170	,9454
			10.000 TL and above	-,83459	,58724	,487	-2,3509	,6817
		10.000 TL and above	Below 2.000 TL	,97143	,74305	,559	-,9472	2,8900
			2001-6000 TL	,64878	,51617	,591	-,6840	1,9816
			6001-10.000 TL	,83459	,58724	,487	-,6817	2,3509

Trust

	Monthly_income	N	Subset for alpha = 0.05
			1
Tukey HSD[a,b]	Below 2.000 TL	30	15,6000
	6001-10.000 TL	76	15,7368
	2001-6000 TL	181	15,9227
	10.000 TL and above	49	16,5714
	Sig.		,384

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 55.230.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Perceived_Usefulness

	Monthly_income	N	Subset for alpha = 0.05
			1
Tukey HSD[a,b]	6001-10.000 TL	76	15,7632
	2001-6000 TL	181	16,3370
	10.000 TL and above	49	16,3469
	Below 2.000 TL	30	17,4333
	Sig.		,110

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 55.230.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Perceived_Risk

	Monthly_income	N	Subset for alpha = 0.05
			1
Tukey HSD[a,b]	2001-6000 TL	181	15,5635
	10.000 TL and above	49	15,6939
	Below 2.000 TL	30	16,6000
	6001-10.000 TL	76	17,0526
	Sig.		,163

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 55.230.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Ranks

	Monthly_income	N	Mean Rank
Trust	Below 2.000 TL	30	156,15
	2001-6000 TL	181	167,10
	6001-10.000 TL	76	163,72
	10.000 TL and above	49	188,64
	Total	336	
Perceived_Usefulness	Below 2.000 TL	30	199,22
	2001-6000 TL	181	167,73
	6001-10.000 TL	76	158,37
	10.000 TL and above	49	168,26
	Total	336	
Perceived_Risk	Below 2.000 TL	30	185,78
	2001-6000 TL	181	155,89
	6001-10.000 TL	76	194,91
	10.000 TL and above	49	163,54
	Total	336	

Test Statistics[a,b]

	Trust	Perceived_Usefulness	Perceived_Risk
Kruskal-Wallis H	2,841	3,883	9,836
df	3	3	3
Asymp. Sig.	,417	,274	,020

a. Kruskal Wallis Test

b. Grouping Variable: Monthly_income