EXAMINING THE USE OF BUSINESS ANALYTICS IN ORGANIZATIONS: AN EXTENSION OF THE TECHNOLOGY ACCEPTANCE MODEL

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ABSTRACT

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Business analytics offers a rich set of benefits that provide significant returns to the organizations. Business analytics systems eliminate the complexity of interpretation of raw data by transforming it into meaningful, accurate, understandable, and shareable information across the organization. Business analytics enables users to make crucial business decisions quickly and reliably by providing the analytical tools that they need to find and interpret information. The main aim of the study is to investigate the factors that affect use of business analytics in the organizations. The factors are examined under three major categories: personal, technological (analysis performance of the system and, interface and integration quality of the system) and organizational (analytical decision-making culture). These three determinants are analyzed under an extended version of the technology acceptance model. This research is focused on shaping possible theoretical and practical implementations of business analytics use in organizations.

Keywords: Business Analytics, Technology Acceptance Model, Analytical Decision-Making Culture, Analysis Performance of the System, Interface and Integration Quality of the System

ÖZ

ÖRGÜTLERDE İŞ ANALİTİĞİ KULLANIMININ GELİŞTİRİLMİŞ TEKNOLOJİ KABUL MODELİ İLE İNCELENMESİ

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İş Analitiği, organizasyonlara çok önemli getiriler sağlayan zengin bir dizi avantaj sunar. Bu sistemler, ham verilerin karmaşıklığını, organizasyon genelinde anlamlı, doğru, anlaşılabilir ve paylaşılabilir bilgilere dönüştürerek ortadan kaldırır. İş analitiği, kullanıcılara çeşitli analitik araçlar sunarak önemli iş kararlarını hızlı ve güvenilir bir şekilde alabilmelerini sağlar. Çalışmanın temel amacı kurumlarda iş analitiğinin kullanımını etkileyen faktörleri araştırmaktır. Faktörler, iş süreçlerinde iş analitiği araçlarının kullanımını etkileyen kişisel, teknolojik (sistemin analiz performansı, sistemin entegrasyon ve arayüz kalitesi) ve organizasyonel (analitik karar verme kültürü) bileşenler olmak üzere üç ana kategoride incelenmektedir. Bu üç unsur, teknoloji kabul modelinin genişletilmiş bir versiyonu ile analiz edilmiştir. Bu araştırma, işletmelerde iş analitiği kullanımının olası teorik ve pratik uygulamalarını şekillendirmeye odaklanmıştır.

Anahtar Kelimeler: İş Analitiği, Teknoloji Kabul Modeli, Analitik Karar Verme Kültürü, Sistemin Analiz Performansı, Sistemin Entegrasyon ve Arayüz Kalitesi

To My Beloved Family

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Undoubtedly it was a compelling journey. At the beginning, the road was filled with uncertainties and complexities. However, then, thanks to so many beautiful people in my life, this rugged road began to flatten and each piece began to unite. As a result, I am proud of this work, and I will be happier when we see its actual contribution in real life. I hope you also enjoy reviewing this work.

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CHAPTER 1

INTRODUCTION

Data has always been very valuable. However, treating data as a measurable entity has changed the world's point of view. Statistics is much more than just being a valuable scientific discipline that is transforming data to knowledge; it gives insight, but most importantly brings value. This is exactly the point of intersection of analytics and business. Being smarter than the others is seen as the secret of success to business. Business analytics became indispensable because it carries this wisdom into business life since it provides competitive advantage (Stubbs, 2011).

Business analytics is different than simple analytics or advanced analytics. The base of business analytics basically consists of them, but it mainly transforms all forms of analytics into business actions. Business analytics can be defined as "the practice and art of bringing quantitative data to bear on decision-making." (Shmueli, Bruce, Yahav, Patel, & Lichtendahl, 2018). Business analytics adds business relevancy, actionable insight, performance measurement and value measurement to the analytics. Once the conversion of data to knowledge is completed, business analytics brings tactical value, creating competitive advantage and supporting corporate strategy (Stubbs, 2011).

Information-assisted management is a highly desirable and efficient way to run a company. For instance, business intelligence systems, one of the most widely used business analytics systems in organizations, with well-integrated analytics techniques serves that purpose. Business intelligence refers to computer-based techniques enables to carry out a systematic process to collect, analyze and disseminate information to support operational and strategic decision making (Hannula & Pirttimaki, 2003). Özçam and Coşkun (2016) state that companies began to use business intelligence at a growing rate and many of non-users are planned to use in the coming years. Mostly, construction, publishing and paper products, and metal goods industries use the business intelligence (Özçam & Coşkun, 2016). An interview was conducted with a company located in the top ten in Europe in the foundry industry. While they are performing operational processes, they have lots of needs to meet in efficient way with high-quality outputs. Handling the complexity of supplier and customer relations, keeping production cost low, controlling the operating costs, increasing the quality of after sales services, dealing with possible declining profits, dealing with new technologies, increasing operational efficiencies and reducing procurement costs are the main aims for every manufacturing company like them. Thanks to the business intelligence software they frequently use, improving operational efficiency and decreasing costs by analyzing profit and loss, controlling all parties including products sales analysis, raw materials, supplier outlays and cost effectiveness of different distributors are all possible (Personal communication, 2018). Another area where business analytics can be applied is job shop scheduling: assigning different works in a sequence to specific machines (Bigus, 1996). Many constraints on scheduling are satisfied by neural networks. Another application area is to quality/quantity control of finished goods (Bigus, 1996). It is implemented by a well-known technique called statistical process control. A further example is to handling complex mixtures of materials used in production where the main purpose is minimizing waste production (Bigus, 1996). Firms are searching for solutions to optimize their complex processes and reduce costs. To sum up, business analytics systems are the key to many complicated problems.

Business analytics applications are currently one of the hot topics in information technology (IT)-related research areas (Parks & Thambusamy, 2017). Business analytics has often been studied from the perspective of computer science. This study, however, will examine the topic from the business perspective: which factors affect the use of business analytics systems in business processes.

Organizations invest in information systems for many different reasons. If all mentioned benefits of business analysis are taken into account, it seems very unreasonable that these systems are not used in organizations. However, studies illustrate that business analytics are not used to a similar extent among organizations, and even among employees in the same organization (DecisionPath Consulting, 2010). Researchers have focused on the factors that could enable to increase the use of information systems into business. In his seminal study, Davis (1986) proposed the technology acceptance model (TAM). Since then, TAM has been tested and expanded several studies in various context such as e-mail usage (Davis, 1986), online shopping (Devraj, Fan, & Kohli, 2002), and interactive TV (Choi et al., 2003). In general, TAM has been experimentally proven to estimate about 40% of the use of a system (Legris, Ingham, & Collerette, 2003). Although TAM has been investigated to examine the adoption of several technologies, there is a scarcity of research that explicitly focuses on business analytics. In order to fill this gap, in this master thesis, TAM is examined in terms of the factors that affect the use of business analytics systems in business processes. The perceived usefulness and ease of use of the system is examined as the most influential factors, positively affecting the attitude toward use. As antecedents of TAM, analysis performance and, interface and integration quality of the system are investigated as technological factors, analytic decision making culture is investigated as an organizational factor. Finally, several personal characteristics, experience level and the effect of system complexity are examined as control variables affecting the actual use of business analytics.

Organizations use business analytics to support their decision making process for both administrative operations and also to ensure critical information is provided in a timely and trustworthy manner. In other words, business analytics is a helpful tool that enables to sustain data-based decision support mechanism in an organization by reaching critical information better, faster, and more reliable. Companies in data-oriented business environments can succeed if their employees are able to make accurate decisions with the help of business analytics. Understanding the business analytics processes leads structured and systematic decisions, thus less error in business situations (Provost & Fawcett, 2013). In this study, business analytics use is investigated under extended technology acceptance model. In the next part of this section, research objectives, the research question and research methods are explained, respectively.

1.1 Research Objectives

In this section of the paper, the objectives of the study are stated under two dimensions: theoretical and practical objectives.

1.1.1 Theoretical Objectives

It is a fact that the value of business analytics has increased and evidence-based management is becoming more and more common day by day. Companies have started to invest and use different analytical tools to make data-based decisions. However, the factors affecting the use of information systems in organizations that enable and support data-based decision-making have not been extensively examined before. Most of the literature investigates the factors for the use of systems that ease operational management and provide simple reporting for organizations, rather than examining the systems that enable business analytics to be used in business processes. Therefore, in this study, the factors affecting use and adoption of a system with business analytics tools have been studied based on technology acceptance model which is one of the most fundamental theories in this respect. In the light of the technology acceptance model, Perceived Usefulness and Perceived Ease of Use were studied as two main factors. In addition, the direct effect of attitude on use was analyzed.

Technology acceptance model mainly engaged in individual factors such as perception and attitude. However, during analyzing the use of business analytics tools, apart from the personal factors, organizational as well as technologic factors play an important role. Considering this fact, this study has two major contributions. Firstly, an organization-related factor Analytical Decision-Making Culture was added to the technology acceptance model as a first antecedent. Secondly, system-related factors; analysis performance and, interface and integration quality of the system were included to the model as second and third antecedents of TAM. All of these factors together were considered as major variables that affecting adaptation and use of business analytics tools in the organizations.

The main objective of this master thesis is to test the technology acceptance model (TAM) in the business analytics context, and contribute to theory development by extending the TAM model via examining organizational and technological level antecedents. Although the impact of business analytics on organizational decision making mechanism is undeniable, fully integration to the evidence-based decision making has not completed yet for all organizations. Thus, it is quite important to gather the most important factors affecting the use and adaptation process to the business analytics tools in order to contribute to the theory. Although this study is generally considered as a theory-testing research since most of the constructs are known, because of the participation of new antecedent factors to the model, this study is also a theory-building research.

1.1.2 Practical Objectives

The adoption of the technology acceptance model developed specifically for business analytics tools will be useful for different parties. Firstly, statisticians, who design the statistical analysis tools, will be able to integrate the most useful business analytics tools into the system to provide benefits to companies. Besides, they will be able to decide more easily which systems need those tools to be integrated. Secondly, the system designers will be able to construct a user friendly design which enables the users to implement more easily. Thirdly, software developers will be able to develop the system in line with the information they receive from statisticians and designers, use their resources in priority areas, use the cost correctly, and early identify possible problems that may arise during implementation. With respect to managerial decision making, this thesis can aid the managers in gaining general understanding of the factors that affect use of business analytics tools. It leads to a successful project management while integrating business analytics tools into any system and a good communication within the users. Thanks to successfully handled user factors into an organization, managers will be able to gain more insights about business practices and costumer behaviors. Business analytics turns unstructured large data sets into better business decisions. Decision-maker can manage the company’s resources, potential investments, and customer relationships well. Thus, operating efficiency will be improved (Elbashir, Collier, & Davern, 2008). In addition, managers will be able to improve predictability by continuously following customer behavioral patterns and market trends. Companies thereby can plan their operations better and deal with uncertainty of business activities thanks to warning system for detecting the symptoms of potential problems in the business patterns. Moreover, companies will be able to act quickly with accurate decisions. Timely decisions give huge competitive advantage in intense, global competition (Min, 2016).

In general, business analytics tools can be integrated into many systems such as customer relationship management (CRM), supply chain management (SCM), enterprise resource planning (ERP), and business intelligence (BI) systems. In addition, there are programming languages and package programs that allow only statistical analysis such as R, Python, SPSS, and Stata. Present study can be used as a preliminary assessment by implementers and practitioners about which user factors are important for the system use and accordingly which actions should be taken in design, development and management phases in order to enable a smooth acceptance and continuous use of the business analytics tools.

1.2 The Research Question

The main aim of this research is to investigate the use of business analytics in the organizations. It is a fact that it is very risky if decisions are made based on gut feeling, intuition, or emotions (Maisel & Cokins, 2015). Therefore, it can be said that rational analysis, independent of human factors, positively influences on the management of organizations and decisions made. Thus, it is a critical point to examine the factors that influence the use of business analytics software by employees in companies that have invested in business analytics. In the light of the main objective, the research question is stated below:

“What are the factors that affect employee’s usage of business analytics applications?”

In order to investigate this issue, the literature addresses that one of the fundamental models is the technology acceptance model (TAM). However, the complexity and variation between revised technology acceptance models are basically known by researchers since TAM is examined for different systems in each study. In this study, TAM is analyzed for business analytics software. In that context, the main constructs in the base model may not be applicable or additional constructs may better explain the actual use of the system. By means of a broad literature review, key factors are examined and hypotheses are formulated.

1.3 Research Method

In this master thesis, in order to meet the study objectives and test the hypothesis, survey research was selected as the research strategy and a questionnaire was administered as the data collection method. The questionnaire has been established mainly based on an extensive literature review. Besides, a pretest has been done and suggestions from academicians and practitioners have been taken into consideration.

The data were collected from small, medium and large-size organizations operating in Turkey. These organizations are operating in a wide variety of industries such as information technologies, finance and banking, regulating, healthcare, chemistry, foundry, petroleum, fast-moving consumer goods, energy, automotive, defense, trade (sales and marketing), and service industry (e.g. human resources, and brand and patent sector). The target group of the survey is employees who are currently using business analytics tools in their business processes.

CHAPTER 2

LITERATURE REVIEW

In this chapter of this research, an extensive literature review is conducted. In the first part, business analytics, its increasing importance and types of business analytics are explained. Then, the contribution of business analytics to decision-making mechanism of organizations is clarified, but also some challenges associated with business analytics are stated. In the second part, the technology adoption model is defined and previous studies related to this model are reported. Accordingly, the factors affecting the use of business analytics are explained and a conceptual model was formulated.

2.1 Business Analytics

Business analytics (BA) is the iterative, methodological study of the available data of an organization, based on statistical analysis (Rouse, 2017). Business analytics is operated by companies to arrive at decisions based on the database in their hands (Rouse, 2017).

In this section, increasing importance, types, contribution to the decision making mechanism of the company and challenges of the business analytics are explained.

2.1.1 Increasing Importance of Business Analytics

In recent years, data has accumulated in the world (Chatfield, 2016). Millions of bits of data are produced every day (Khoso, 2016). Databases store data in gigabytes or even terabytes (Williams, 2014). There is no point in storing data in these huge sizes unless we interpret its meaning. We live in such an era that only the ones who use the data wisely can achieve success. If users, especially companies can analyze this data properly, they can extract useful information and knowledge from it. Since meaningful information is used for companies' welfare and profitability, it finally creates a competitive advantage.

With the massive growth in available data, and the growing dedication of strategic management in the companies, focus on evidence-based practices has increased. Thus, it has brought the necessity of using analytics techniques, and has led to the emergence of *Business Analytics* (Acito & Khatri, 2014). Business analytics is defined as “the integration of disparate data sources from inside and outside the enterprise that are required to answer and act on forward-looking business questions tied to key business objectives” (Isson & Harriott, 2013, p.3) or more simply “evidence-based problem recognition and solving that happen within the context of business situations” (Holsapple, Lee-Post, & Pakath, 2014, p.134). Business analytics creates a two-way loop between operations and analysis that enables data to be analyzed and the analysis results are transferred in business actions. The emerged information which is developed in that loop is used by business users in its everyday activities (Kohavi, Rothleder, & Simoudis, 2002).

The concept of “Business Analytics” emerged when Frederick Winslow Taylor presented *Scientific Management* context in his book “Principles of Scientific Management” in 1911. However, it began to reach its peak when the scholars of information systems (IS) community launched the smart systems known as “Decision Support System” in 70's. Analytics started to be conducted by pen and paper, and it continues to be performed with various methods like extremely sophisticated modules such as SAS modules that present complex explanatory and predictive models (Ahmed & Ji, 2013). Nowadays, International Data Corporation (IDC) states that business analytics revenues are forecasted to be grown from $130.1 billion in 2016 to more than $203 billion in 2020 (Press, 2017).

P&G, one of the major FMCG companies, has a successful business analytics integration story (Murphy, 2012). P&G operates in 180 countries with 127,000 employees and over 300 brands. P&G has approximately 4 billion transactions, daily. In order to "digitize" the business processes and centralize the decision-making mechanism, they launched the analytical systems named Business Sufficiency, Business Sphere and Decision Cockpits. These analytical solutions serve to thousands of users. They did cost reduction in many areas to invest in business analytics. Only IT department has cut $900 million costs and eliminated almost 1,600 non-manufacturing processes. Their CIO stated that they would like to quadruple the number of business analytics experts because they mainly would like to change the way of using data to run the company (Murphy, 2012).

In 2010, P&G firstly started to use Business Sufficiency program which predicts P&G's market share and various performance statistics for the next 6 to 12 months. The software mainly answers what is happening now, why it is happening, and what kind of actions they can take. The "what" question uses the sales, market share and logistics data. P&G handles the what problem by letting 58,000 employees use business intelligence "cockpits" which provides dashboards that allow to monitor all necessary information. The "why" question drills sales data down to the country, region, store levels, consumer behavior, advertising and economic factors. The "actions" affect pricing, advertising, and product mix decisions. Business Sphere program deals with approximately 200 terabytes of data for further detailed analysis and visualization. The presented results reveal insights, trends, and opportunities for the executives and allow them to ask very focused business questions (Murphy, 2012).

P & G is supporting analytical and data-based decision-making within the company by using business analytics systems. Employees have improved many business processes and provided savings. Until then, managers who were not aware of the importance of business analytics, are now willing to use deep analyzes for their projects (Davenport & Harris, 2007).

As another example, CVS Health, a successful pharmaceutical company, decided to launch a call center program. They used "predictive behavior routing" which means they segmented their customers into six different behavior groups. At the same time, they keep scores of the call center representatives in order to ensure the best interaction with the customers. This practice reduced call time and developed customer relationships (Laskowski, 2015).

A further example is what Facebook does. They utilize a huge social network to predict possible preference patterns. They can handle great number of pieces of demographic information and user activities. Data scientists at Facebook say that they are even able to predict a possible romantic relationship that will emerge by looking at the connections and communication patterns. It was hard to believe, but it is possible with business analytics (Mishra, 2017).

In 2015, business analytics spendings were $ 6.4 billion in financial sector; $ 2.8 billion in government sector, $ 1.2 billion in media industry; and $ 800 million in energy and utility services. Researchers predict that the annual investments in business analytics for only these sectors would rise from 22% to 54% towards 2020 (Villanova University Business Articles, n.d.). In conclusion, the importance organizations give is growing day by day and is expected to grow even further.

In the next part of this section, the types of business analytics are briefly introduced.

2.1.2 The Types of Business Analytics

Data is processed at various steps under the different stages of business analytics. There are three main business analytical types, depending on the workflow phase and the need for data analysis (Mehta, 2017). These three types answer everything that a company needs to know from what happens in the organization to what solutions to adopt in order to optimize the processes (Mehta, 2017).

Three types of business analytics are generally applied in stages and one of them is not superior to another. They are related to each other and each of them presents a different understanding (Mehta, 2017).

In this section of the paper, these three types of business analytics are introduced and enriched with examples.

2.1.2.1 Descriptive Analytics

Business analytics begins with descriptive analytics which is basic statistics that allows managers to see structured and customized reports, detect the situations, identify patterns and trends, and find problems or opportunity areas (Evans & Lindner, 2012). Descriptive analytics also covers diagnostic analytics. Banerjee, Bandyopadhyay and Acharya (2013) explain diagnostic analytics stage as interpretive about ‘why’ particular cases are encountered in an organization, generally aims to find out the root causes of a problem, and it could be either exploratory or confirmatory. Diagnostic analytics is generally used to discover the business environment, the customers, the risks associated with a new product, etc., briefly in strategic decisions (Banerjee et al., 2013). Overall, descriptive analytics deals with what happened in the past and why (Ransbotham, Kiron, & Kirk Prentice, 2015). However, the advanced analytics begins with the second phase of the business analytics which is called predictive analytics.

2.1.2.2 Predictive Analytics

Predictive analytics uses historical data in order to predict the future by examining patterns, detecting relationships in the past data, and adjusting patterns/relationships of future time (Evans & Lindner, 2012). Eckerson (2007) clarifies predictive analytics applications on companies in the field of forecasting about the processes, better understanding customer behavior, identifying business opportunities, and possible problems before they happen. Since predictive analytics are used for such significant tasks, *predictive accuracy* of the used system must be ensured. Shmueli and Koppius (2011) investigated related studies in the most reliable journals, MIS Quarterly (MISQ) and Information Systems Research (ISR), and illustrated that researchers were curious about whether predictive accuracy is mostly based on sampling techniques, adequate predictive methods, or explanatory power measures such as p-value and coefficient of determination (R^2). It should be stated that all these criteria are the ones with high impact on predictive performance. The conduct of such investigations is important for the productivity of systems containing predictive analytics since companies' benefits of the predictive model is highly related with the prediction accuracy and, unfortunately costs are associated with prediction error (Shmueli & Koppius, 2011). Therefore, prediction accuracy should be kept high and prediction error should be kept low for any system including prediction analytics.

As an example, Aronsson (2015) discusses different business situations of some predictive studies that were conducted for different purposes on a company called Klarna. Klarna works with Attollo, a consulting firm which is specialized in corporate performance management, and Attollo uses software called IBM: SPSS Modeler for predictive analytics. IBM divides predictive analytics into three subheadings: Customer, Operational, and Threat and Fraud analysis. An effective customer analysis helps preventing unnecessary costs and increasing customer satisfaction. Based on this aim, it is important to understand how to satisfy and retain loyal and profitable customers, to attract others like them, to know the factors that keep the customers, and to increase the profitability of each customer by understanding customer preferences and how willing a customer is to buy (Aronsson, 2015). Operational analytical strategies aims to identify and solve problems in the product life cycle beforehand so that possible failure process can be managed more effectively, thereby foreseeing maintenance period to avoid and reducing warranty claims (Aronsson, 2015). In addition, it determines to make sales forecasts as reflections of a successful operation (Aronsson, 2015). For threat and fraud analysis, it is important to know what constitutes normal and unusual behaviors, to identify suspicious activity at an early stage, to increase customer satisfaction by meeting claims more quickly, and to increase the response time by placing the officers at the right place and at the right time (Aronsson, 2015). The result is that the predictive analytics allows Klarna to better understand its operational performance, customers and external environment, therefore make better decisions (Aronsson, 2015).

2.1.2.3 Prescriptive Analytics

The final type of business analytics is prescription analytics, which is a set of analyses to improve business performance under the presence of complex goals, requirements and constraints. The main role players in prescription analytics are optimization modeling, simulation modeling, multi-criteria decision modeling, expert systems and group support systems. The most important output of this analysis is the set of knowledge that provides the best possible course of business decisions i.e. actions for a given situation (Delen & Demirkan, 2013). As one of its main tasks, prescriptive analytics is used for optimization to determine the best alternatives in many different areas of business, including marketing, finance and operations (Evans & Lindner, 2012). To maximize revenue, companies can determine the best pricing decisions and set most attractive advertising strategy, the optimal amount of cash can be deposited at ATMs, or the best combinations can be selected among a variety of investment options in a portfolio for risk management (Evans & Lindner, 2012). As a continuation of the optimization modeling, sensitivity analysis ensures the accuracy of the predictive component of analysis, i.e. multiple regression model, hence affects the prescriptive component, i.e. the optimization model (Kawas, Squillante, Subramanian, & Varshney, 2013). When the regression model is more accurate, optimization model, that is prescriptive recommendations, will provide more reliable solutions. The intent of the sensitivity analysis is to check the robustness of the prescriptive recommendations over variations in the regression parameters. According to the sensitivity analysis about a company's salesforce conducted by Kawas et al. (2013), optimal total revenue may vary, optimal number of headcount for each vendor category may vary, or both may vary. The interaction between the two conditions is analyzed in optimization model of company's salesforce and the results were made more robust. Another main analysis regarding prescriptive analytics is multi-criteria decision modeling. For instance, it is widely used in supplier selection and evaluation processes (Ho, Xu, & Dey, 2010). Firms deal with numerous quantitative and qualitative factors such as price, cost, product quality, delivery speed, supplier flexibility. Thanks to multi-criteria decision modeling approach, companies can solve the supplier selection and evaluation problem effectively (Ho et al., 2010).

Prescriptive analytics is the most advanced form of analytics since it has an enormous influence on business objectives like profit, costs, service quality, and risk management (Gröger, Schwarz, & Mitschang, 2014). The main reason of its large impact is that it is basically providing optimization to the company on various processes.

2.1.2.4 Conclusion

Business analytics is used to get insights about several business situations, make business decisions easily, and to automate and optimize business processes. Data-driven companies treat their data as a corporate entity and use it for competitive advantage. Successfully implemented and applied business analytics depends on data quality, talented employees who understand technology and processes, organizational commitment to evidence-based decision making (Rouse, 2017; Davenport, 2006).

Business analytics contains deeper statistical analysis. Certain types of business analytics are composed of *descriptive analytics*, *predictive analytics*, and *prescriptive analytics*. Descriptive analytics helps to evaluate the present state of a business. Predictive analytics is used to apply statistical algorithms to historical data to make a prediction about any situation and analyzes trend data to estimate the probability of future outcomes. Prescriptive analytics uses past or present data to provide recommendations about how to deal with similar situations in the future (Rouse, 2017). All these types of business analytics could be useful for companies; however, it is not clear yet which of them are most popular or whether companies can effectively use all of them together and reflect them into their business processes.

2.1.3 The Impact of Business Analytics on Decision Support Mechanism of the Companies: Analytical Decision-Making

Business analytics has been defined as "a process of transforming data into actions through analysis and insights in the context of organizational decision making and problem solving" (Liberatore & Luo, 2010, p.314). As it can be understood from the definition, one of the primary purposes of business analytics is expected to be on decision-making processes and improvements in organizational performance are likely to be an outcome of superior decision-making processes enabled by business analytics (Sharma, Mithas, & Kankanhalli, 2014; Davenport, 2006).

Jindal, Sharma, and Sharma (2014) likened a system based on business analytics to a ”basketball coach during a basketball match through suggesting tactical solutions based on the data of the past games” (p.44). According to Christoffersson and Karlsson (2015), business analytics gives insights to employees and supports their decision through data and evidence. *Decisional paradigm* is a concept that means decisions are based on evidence, in our case, based on business analytics. On the other hand, many decisions are still made based on experience and intuition. However, biases in human judgement can lead to many problems in business life and it necessitates the use of business analytics. Christoffersson and Karlsson (2015) state that decisions based on data and intuition represent double-edged dimensions of decision making; and intuition-driven decision is thought as rapid and experience based and data-driven decision is deep and takes a lot of time. Thus, according to Jindal et al. (2014), in addition to its many benefits, data-driven decision has some disadvantages. Most important one is complexity of the tools. If it is not designed user-friendly, it may not be directly used by business users although it is produced for them. That is why, new approach was introduced for business users and other decision makers, enabling them to view and exploit business analytics tools.

In spite of the fact that business analytics tools have some complexity issue, its return should be taken into consideration. According to Mansell (2015), “the major costs of information are in its capture, storage and maintenance - the marginal costs of using it are almost negligible.” (p.18). Mansell (2015) states that better performing organizations are related to the level of usage of business analytics. They form similar type of reports however, in the background; these reports are composed of reliable rational data analysis. As a matter of fact, Mansell (2015) explains that if managers do not use analytics in strategic decision making, the organization will not sustain its competitive advantage and efficiency on their operations. In conclusion, business analytics greatly influences by the decision-support mechanism of companies, and also it supports the development of data-based and analytical decision making processes within the company.

2.1.4 Challenges of Business Analytics

There is no doubt that a system with business analytics is quite useful, but it always has some challenges in a broad sense (Isson & Harriot, 2013). In terms of the use, the keystone of the systems is the business users (Kohavi et al., 2002). The human factor is indeed the greatest reason of why these challenges arise. Firstly, there is insufficient number of data-literate employees for good use of the data (Isson & Harriot, 2013). Smart and knowledgeable data professionals are crucial to good management of the data. McKinsey Global Institute (2011) report shows that only US needs approximately 1.5 million more data-literate managers to have enough number of the data-driven organizations. The whole world needs much more. Secondly, driving business processes with business analytics is a major technological shift in the organizations (Davenport & Harris, 2007). It leads to some organizational changes in many respects. Key corporate assets like core competencies, financial and human assets are managed digitally (Laudon & Laudon, 2018). In terms of organizational structure, technological shift makes organizational pyramid flattered because systems increase manager's span of control (controlling subordinates) and systems take the absorption task from middle level so companies have less need middle managers. Those changes may have impact on job design of employees (job responsibilities, work tasks, process structures etc.). It is a critical challenge for organizations to manage the technological shift well and make a smooth transition. Thirdly and most importantly, one of the major challenges is user-resistance to the system. Companies develop some strategies to overcome user resistance such as conducting trainings, using top manager support, giving incentives or monetary awards, and ensuring user involvement to the system. Present research will be a lodestar study to handle these challenges by developing a model of the motivational factors connecting system features with actual use of business analytics in organizations since these challenges are overcome and benefits of the systems are achieved only if end-users are successfully adapted to the system (Davis, 1985).

2.2 A Fundamental Model That Explains System Use: Technology Acceptance Model (TAM)

Technology acceptance model is an information systems-related theory that models how users adopt and use a technology. It is one of the widely used models for explaining the factors on user acceptance of information systems with the greatest influence (Suh & Han, 2002). In this part of the study, technology acceptance model is clarified in detail and major studies on business are examined.

2.2.1 Technology Acceptance Model (TAM)

Companies make investment decisions about information systems for many motivations. Researchers have done many studies to determine the factors that influence the use of technology and enable the proper integration of the system into business processes. In the early 80's, initial researches revealed number of factors such as perceived utility, job effect, response/turnaround time and security of data (Bailey & Pearson, 1983). Then, researchers tried to develop a model to explain the relationships between those factors and predict the use of system. As one of the most fundamental studies, Davis (1985) has constructed the Technology Acceptance Model (TAM), which is a theoretical model that explains how system users accept an information system and which factors mainly affect a technology acceptance. TAM was mainly built and developed on the Fishbein (1967) model. It was used as a base theory and it was extended as the theory of reasoned action (TRA) by Fishbein and Ajzen (1975) which is aimed to explain the shown behaviors in a specific situation (Figure 1). According to Fishbein and Ajzen (1975), intention to perform a specific behavior depends on attitude toward the behavior and subjective norm regarding the behavior.

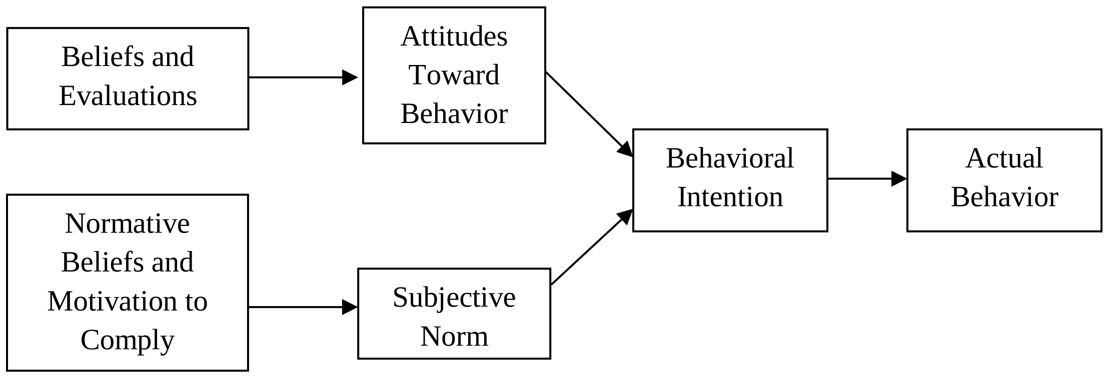

Figure 1. *The Theory of Reasoned Action (TRA)* Adapted from Fishbein, M. & Ajzen, I. (1975). Belief, attitude, intention and behavior: An introduction to theory and research. Reading, MA: Addison-Wesley.

Technology acceptance model (Davis, 1985) explains the factors affecting the use of a system and the relationship between those factors. Use of the system means individuals' direct usage of the given system within the scope of own's job. Actual use of a system is assumed as a continuously repeating action with respect to a specific system and in a specific context (in user's job) (Fishbein & Ajzen, 1975). A possible user's attitude toward a system and intention to use are modeled as primary determinants of the user's actually use it. On the other hand, attitude toward use depends on perceived usefulness and perceived ease of use of the system. Perceived ease of use has a causal effect on perceived usefulness. External variables directly influence perceived usefulness and perceived ease of use. External variables do not have the direct effect on attitude or behavior, but affect indirectly through perceived usefulness and perceived ease of use (Davis, 1985). TAM is shown in Figure 2.

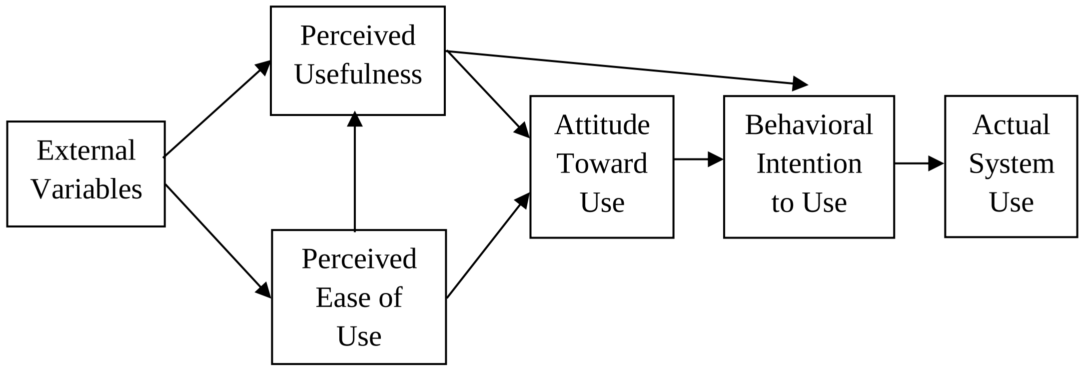

Figure 2. *Technology Acceptance Model* Adapted from Davis, F. D. (1985). A Technology Acceptance Model for Empirically Testing New End-User Information Systems. Massachusetts Institute of Technology.

2.2.2 The Key Studies Examining TAM and Their Findings

After its original version on constructing the model on the use of electronic mail (Davis, 1985), TAM has been tested, extended or narrowed multiple times while examining various technological systems (Legris et al., 2003). Among these researches, adapted technology acceptance models used in reviewing business application tools will be examined in this section. Technological systems outside business context will be ignored due to the concept of this research.

Davis's (1993) another study concerned the user's reactions to the managerial computer use. According to Davis, the actual use is mainly predicted from their intentions and intention depends on majorly perceived usefulness and then perceived ease of use. Perceived usefulness was 50% more effective than perceived ease of use (Davis, 1989; Davis, 1993). For predicting user intentions to spreadsheets in an office environment, Mathieson (1991) compared two theories, the technology acceptance model with the theory of planned behavior (TPB) which proposes that attitude toward specific behavior, subjective norms, and perceived behavioral control form behavioral intentions and actual behaviors. In this context, Mathieson stated that TAM gives only general information and easy to apply and test, but TPB provides more detailed information for developers. Subramanian (1994) said that the only factor that influences the future use of voice mail system and customer dial-up system is perceived usefulness. Unlike Davis (1985), Szajna (1996) found that perceived ease of use and perceived usefulness affect behavioral intention to use do not have direct effect on actual use of electronic mail. Jackson, Chow, and Leitch (1997) justified that situational involvement has negatively direct effect on behavioral intention and attitude, attitude is a mediator, and intrinsic involvement influences shaping perceptions on the use of spreadsheet, database, word processor and graphics tools. Agarwal and Prasad (1999) mentioned that individual differences in the work environment (education level, experience level, and participation in trainings) significantly affect on intentions and actual use of a system includes word processing, spreadsheet and graphics. Lucas and Spitler (1999) believed that social norms in an organization and the nature of the job are more important influencers of the use of the technology rather than the user's perceptions of the technology for multifunctional workstation systems. Venkatesh and Morris (2000) suggested that perceived usefulness explains the actual use more than use intentions. In addition, the social influential factors such as social norms, voluntariness and cognitive instrumental factors such as job relevance, output quality, and perceived ease of use have significant effect on user acceptance for data and information retrieval systems. Lee, Hsieh and Hsu (2011) have examined e-learning system acceptability in organizations. They proposed an extended technology acceptance model by combining the innovation diffusion theory (IDT) with the technology acceptance model (TAM). Compatibility, complexity, relative advantage, and trialability significantly affect perceived usefulness and perceived ease of use. Bajaj and Nidumolu (1998) stated that experience in use of a system obviously influences the perceived ease of use and it is the main factor in user's future use for management information systems and production control tools.

Amoako-Gyampah and Salam (2004) extended the TAM by adding the three factors shared beliefs in the benefits of an ERP system, system training and project communication in the context of an ERP implementation. Bueno and Salmeron (2008) have chosen a different way of examining the technology acceptance model for ERP. They have identified certain critical success factors and examined the influence of these factors on TAM and hence the acceptance of ERP. Specifically, the factors have been stated as top management support, communication, cooperation, training and technological complexity of ERP systems. Some of these factors mainly affect the behavioral intention to use an ERP system. According to the findings, firstly, organizations should involve potential users in the ERP implantation stage. It enhances the communication between practitioners and the actual use. Secondly, organizations should select an ERP with little complexity and training is considered to be the main action. Both low complexity and training factors positively affect the perception of an ERP system's ease of use. Thirdly, top management support should be visible in the organization during the first implementation and the actual use of ERP. As a complete model, the constructs of top management support and communication are not directly related to TAM variables. These factors only change users' perceptions towards the use of ERP and thus positively influence the attitude toward use through cooperation (Bueno & Salmeron, 2008). Çalışır and Çalışır (2004) have studied on ERP use in organizations and adapted TAM to predict end-user satisfaction by adding new variables such as system capability, user guidance and learnability to the perceived usefulness and ease of use variables, which are the main factors of the technology adoption model. Significant findings of this study are high system capability and user guidance positively affect perceived usefulness and with a good user guidance will improve the learnability. Among these variables, perceived usefulness has the strongest influence on end-user satisfaction and learnability has a relatively smaller effect on end-user satisfaction with ERP systems. Kwak, Park, Chung, and Ghosh (2012) have studied on TAM by adding internal and consultant support and system functionality constructs for usage of ERP in project-based sectors. They found that consultant support affects negatively perceived usefulness. Paşaoğlu Baş (2017) studied on the factors affecting the use of ERP systems by using the TAM, and in addition to usual overlapped findings, she has found that a positive effect exist on the possibility of using ERP if the company is innovative, supports employees, prone to cooperation and team goals. Besides, the research revealed that while employees with age ranges of 22-40 employees in the institution are willing to use ERP systems, older employees who are in their 40s are either undecided or reluctant to use it.

Money and Turner (2005) investigated the classical variables in TAM to explain knowledge management systems (KMS). The perceived usefulness and perceived ease of use account for 51% of the behavioral intent to use the system, and intention positively leads the use of KMS. Dulcic, Pavlic, and Silic (2012) have found that perceived ease of use is more relevant factor than perceived usefulness contributed to their job tasks when using decision support system (DSS) in mandatory settings. The main reason for this result is that users are not voluntarily using it, but are forced to use the system that the company owns. Bach, Čeljo, and Zoroja (2016) had a fresh look to the implementation of business intelligence systems (BIS) by using and extending TAM. They proposed that technology driven strategy, high information quality and, good project management enhance perception of usefulness and ease of use of BIS by users. Moreover, project management is influenced by change management in the process and knowledge sharing between the parties during and after the implementation. Serçemeli and Kurnaz (2015) observed that the tax inspectors' perceived ease of use in the process of using information technology in the audit process is affected the attitude toward behavior positively. In other words, if tax inspectors are able to use information technology products easily, it can be said that they will show a positive attitude toward using these products. Tax inspectors' perceived benefit in the formation of behavior towards information technology use in the audit process seems to positively influence intention to use. In other words, if tax inspectors find the information technology products they use to be useful, they can be said to intend to use these products. In addition, there was no difference between perceptions of tax inspectors and TAM components in terms of age and work experience (Serçemeli & Kurnaz, 2015).

In general, TAM has proven to be a very useful and popular context for clarifying and predicting system use (Chuttur, 2009). It is known as the most cited and one of the most influential models to recognize the acceptance of information technology (Wang & Liu, 2005). Until now, there have been several studies about TAM and research results have been observed to be consistent over the years (see Table 1 and Table 2). As discussed in this section, many systems which are get into use by organizations have been tested with TAM. However, no study has been conducted specifically on new emerging business analytics tools. It may be difficult to improve the estimated predictability of TAM if a wider model including organizational and social

Table 1

Review of Studies on TAM

Study	Context	Model Used
Davis, 1985*	E-mail	TAM + TRA
Davis, 1993*	Managerial computer use	TAM
Mathieson, 1991*	Spreadsheets	TAM + TPB
Subramanian, 1994*	Voice mail and customer dial-up system	TAM
Szajna, 1996*	E-mail	TAM
Jackson, Chow, & Leitch, 1997*	Spreadsheet, database, word processor, graphics	TAM
Agarwal & Prasad, 1999*	Word processing spreadsheet graphics	TAM + Individual Differences
Lucas & Spitler, 1999*	Multifunctional workstation	TAM + Social Norms and Perceived System Quality
Venkatesh & Morris, 2000*	Data and information retrieval	TAM + Subjective Norms, Gender and Experience
Lee, Hsieh, & Hsu, 2011	E-learning system	TAM + IDT
Bajaj & Nidumolu, 1998*	Debugging tool	TAM + Loop Back Adjustments
Amoako-Gyampah & Salam, 2004	ERP	TAM + Shared Beliefs in the Benefits, Training, Project Communication
Bueno & Salmeron, 2008	ERP	TAM + Critical Success Factors
Çalışır & Çalışır, 2004	ERP	TAM + System Capability, User Guidance, Learnability
Kwak, Park, Chung, & Ghosh, 2012	ERP	TAM + Support, System Functionality
Paşaoğlu Baş, 2017	ERP	TAM

Table 1 (cont'd)

Study	Context	Model Used
Money & Turner, 2005	KMS	TAM
Dulcic, Pavlic, & Silic, 2012	DSS	TAM
Bach, Čeljo, & Zoroja, 2016	BIS	TAM + Technology Driven Strategy, High Information Quality, Good Project Management
Serçemeli & Kurnaz, 2015	IT use in the audit processes	TAM

*(Yousafzai, Foxall, & Pallister, 2007)

Table 2

Relationships Found Between the Key Factors within the Scope of TAM

Study	PEU-PU	PU-ATU	PEU-ATU	PU-BI	PEU-BI	ATU-BI	ATU-AU	BI-AU	PEU-AU	PU-AU
Davis, 1985*	✓	✓	✓				✓			✓
Davis, 1993*	✓	✓	✓				✓			✓
Mathieson, 1991*	✓	✓	✓	✓		✓				
Subramanian, 1994*	×			✓	×					
Szajna, 1996*	✓			✓	✓			✓	×	×
Jackson, Chow, & Leitch, 1997*	×	×	✓	×	✓	×				
Agarwal & Prasad, 1999*	✓	✓	✓				✓			✓
Lucas & Spitler, 1999*	✓			×	×				×	×
Venkatesh & Morris, 2000*	✓			✓	✓					
Lee, Hsieh, & Hsu, 2011	✓			✓						

Table 2 (cont'd)

Study	**PEU-PU**	**PU-ATU**	**PEU-ATU**	**PU-BI**	**PEU-BI**	**ATU-BI**	**ATU-AU**	**BI-AU**	**PEU-AU**	**PU-AU**
Bajaj & Nidumolu, 1998*	✗	←	✓				✓			✗
Amoako-Gyampah & Salam, 2004	✓	✓	✗	✗		✓				
Bueno & Salmeron, 2008	✓	✓	✓	✓		✓				
Çalışır & Çalışır, 2004	✓									
Kwak, Park, Chung, & Ghosh, 2012	✓			✓	✓					
Paşaoğlu Baş, 2017									✓	
Money & Turner, 2005	✓			✓	✓			✓		
Dulcic, Pavlic, & Silic, 2012	✓			✓	✓			✓		
Bach, Čeljo, & Zoroja, 2016	✓									
Serçemeli & Kurnaz, 2015		✗	✓	✓		✗		✗		

Note. blank: the relation was not measured, ✓: a significant and positive relation was found, ✗:non-significant relation was found, ←: a significant but reverse relation was found

*(Yousafzai, Foxall, & Pallister, 2007)

factors is not proposed (Legris et al. 2003). In this thesis, we aim to fill this gap by examining individual, organizational, and technological factors.

2.3 Factors Affecting the Use of Business Analytics in Business Processes

In this section of the research, factors impacting the use of business analytics systems in business processes, in particular attitude toward use, are explained and hypotheses are formulated based on the literature review.

2.3.1 Attitude Toward Use

Attitude is defined as "an individual's positive or negative feelings about performing the target behavior" by Fishbein and Ajzen (1975, p.216) and attitude toward use of the system implies the degree of evaluation effect of an individual about using the related system (Fishbein & Ajzen, 1975). In addition to attitude towards use, Davis (1985) also used behavioral intention to use construct on TAM. In the study of Legris et al. (2003), it is revealed that only 32% of the studies included both attitude and intention in the model. As majority did, only attitude is investigated in this research (Legris et al., 2003).

According to TAM, the general attitude of a potential user to use a particular system is hypothesized to be the main determinant of whether he or she uses it. On the other hand, attitude toward use is believed to be affected by two main factors: *Perceived Usefulness* (decisional relevance) and *Perceived Ease of Use* (understandability) (Davis, 1985). Researchers generally examined the direct attitude-behavior relationship before the Fishbein intention model was initiated (Wicker, 1969), and continued to better understand the moderators and factors for which attitudes predict behavior (Davidson & Jaccard, 1979; Fazio & Zanna, 1978). After Davis (1989) published that attitude toward use has a significant effect on the actual use of a system, dozens of studies have continued to prove the truth of this relationship.

Davis (1993) states the significant relationship between attitude and actual use. Davis, Bagozzi, and Warshaw (1989) say that attitude have little influence while mediating between perceptions and actual use. Taylor and Todd (1995) argue that attitude is not an important predictor of intention to use the system. Jackson et al. (1997) state that the direct effect of attitude on behavioral intention is statistically significant, but in the negative way. In this study, attitude plays a mediating role through intention, as well. Igbaria's study (1993 and 1994) claims that attitude has moderation effect on behavioral intention. In the same way, Bajaj and Nidumolu (1998); Al-Gahtani and King (1999); Al-Gahtani (2001); Roberts and Henderson, (2000); Handy, Whiddett, and Hunter, (2001); Suh and Han (2002); Lee, Cho, Gay, Davidson, and Ingraffea (2003); Olson and Boyer (2003) discuss whether positive attitude toward use increases the level of actual use and they all found significant relationship.

Combining all of the views, hypothesis 1 has been constructed:

Hypothesis 1: A positive attitude toward using the business analytics tools leads to a higher level of use of business analytics tools in business processes.

2.3.2 Perceived Usefulness and Perceived Ease of Use

There are some reasons for people accepting or rejecting an information technology. Among the many reasons that could affect the use of the system, previous research has identified two major determinants (Davis, 1989). One of the most important factors that affect the actual use of a system is *Perceived Usefulness*. Davis (1989) defined *Perceived Usefulness* as "the degree to which an individual believes that using a particular system would enhance the job performance." (p. 320). Employees are willing to use a system or a tool if they believe it will assist them to do their job tasks. A system with high perceived usefulness provides high usage performance for users (Davis, 1989). In addition, there is also a significant relationship between perceived usefulness and attitude toward use a system. One of the most important contributions in this area belongs to Ajzen and Fishbein's (1977). According to them, strong attitude-behavior relationship is obtained only if there is a high relevance between goals and actions in attitude and behavioral issues. In an organization, business analytics is used for many different purposes. Among these purposes, the most important one is to make decisions that will add value to the organization. If the system users within the organization regularly use the tools for organization's strategical decisions, and if they get successful returns, their attitude will evolve in the positive direction. Thus, if the user believes that business analytics is useful for the welfare of the organization, their attitude will develop positively.

Secondly, even if a system is very useful, potential users can also believe that it is very difficult to use and the effort of using the system outweighs the benefits (Davis, 1989). Thus, in addition to its usefulness, the attitude toward use and actual use are influenced by the *Perceived Ease of Use*. *Perceived Ease of Use* is described as "the degree to which an individual believes that using a particular system would be free of physical and mental effort." (Davis, 1989, p. 320). Effort is the limited resource which an individual can make for various activities (Radner & Rothschild, 1975). It is claimed that it is more likely that a user will accept an application that is easier to use than others (Davis, 1989).

Perceived usefulness is highly related to system design and features. The characteristics of the system, actually, affect the usefulness indirectly by affecting the ease of use. While a design feature increases its usefulness, it can also reduce its ease of use, compensatory perceptual effects cancel each other and prevent any positive change in use of a system (Davis, 1989).

Some inferential processes may influence ease of use perceptions since subjects may get trainings or, it should be taken into account their own abilities and past experiences for mastery of the certain system. However, perceived usefulness is considered much more inferential; this requires that the subjects anticipate the impact of the system on business performance in the case of without any experience of the system (Davis, 1989).

According to Davis (1993) and Agarwal, Prasad, and Zanino (1996), compared to the usefulness, the perceived ease of use has a quite small effect. The perceived usefulness is 50% more effective than the ease of use in determining the system use (Davis, 1993). This conclusion emphasizes the importance of using appropriate functional capabilities in systems (Davis, 1993). Another striking result that Davis conclude is that while usefulness might reflect concerns about both benefits and costs of using a system, ease of use is seen as only cost, from the point of view of the user. Therefore, usefulness is seen as more dominant effect on attitude and use. Hu, Chau, Liu Sheng, and Yan Tam (1999) state that while perceived usefulness is a significant determinant of attitude and intention, perceived ease of use was not found as a significant factor. This time, Karahanna, Straub, and Chervany (1999) examined the phase of adopting technology in two different stages. While attitude during pre-adoption is mainly based on perceptions of usefulness, ease of use, display of the results, and triability; post-adoption is solely related to perceived usefulness and image enhancements. Igbaria's study (1993 and 1994) claims that perceived usefulness has a positive effect on attitude, and actual use. Positive attitude towards the use of the system is determined jointly with perceived usefulness and ease of use (Phillips, Calantone, & Lee, 1994). Taylor and Todd

(1995) state that while the relationship between perceived usefulness and attitude is significant, path from ease of use to attitude is not significant. In predicting user acceptance of a technology, although some studies have demonstrated the predominance of perceived usefulness over ease of use (Davis, 1993; Agarwal et al., 1996; Agarwal & Prasad, 1999), Loh and Ong (1998) show that this situation does not always have to be observed. The importance of ease of use of a system should not be ignored. If system is easy to use, it plays an undeniable role in determining user's attitude. Additionally, the effect of perceived ease of use on perceived usefulness was investigated and usually found as significant (Lu & Yeh, 1998; Agarwal & Prasad, 1999; Lu, Yu, & Lu, 2001; Townsend, Demarie, & Hendrickson, 2001). Benamati and Rajkumar (2002) examined outsourced decision support system and they found that decision makers' attitude plays an important role in the decision-making process. For the action of outsourcing decided by decision makers, the greater benefits brings and the easier usage is ensured, the more likely decision-makers will consider to do it (Benamati & Rajkumar, 2002). Davis argues that usefulness mediates the relationship between ease of use and attitude. The ease of use is also regarded as the first benefit of the system brings to the user. If the system is easy to use, users spend shorter time in the system, thus they can devote all their efforts and allocate more time to their job tasks (Davis, 1989; Riemenschneider & Hardgrave, 2003). To conclude, the most of the results are consistent with the TAM-associated studies.

According to the findings, the direct effect of perceived usefulness and perceived ease of use on the attitude toward the use of a system will be investigated in this paper. In addition, as the base model of Davis (1989) is proposed, the effect of the perception of easy to use on usefulness will be analyzed. All three relationships are proven also by Davis (1993). In line with these offerings, the following hypotheses have been formulated:

Hypothesis 2: If the user perceives the business analytics system as useful, a positive attitude toward the use of the system will be developed.

Hypothesis 3: If the user perceives the use of the business analytics system as easy, a positive attitude toward the use of the system will be developed.

Hypothesis 4: If the user perceives the use of the business analytics system as easy, it leads to be perceived as useful of the business analytics tools for the users.

2.3.3 Analytical Decision-Making Culture

Organizations are willing to invest in decision support systems in order to improve the given support to decision-makers. However, instead of only purchasing a system to use, it is more crucial to successfully manage the change management. These systems should be successfully implemented in each unit of the organization and especially top managers should develop a policy that supports incorporation with systems and business processes. For this reason, in order to effective use of business analytics systems in organizations, organizations should not only deal with the system installation but also implement information management practices, information sharing and information integrity. This management should be combined an environment in which the decision-making is based on rationality, i.e. the information is always analyzed in a comprehensive way (Popovic, Hackney, Coelho, & Jaclic, 2012).

Decision making mechanism in organizations has been investigated for a while. Basically, decision makers are classified as right hemisphere orientated (intuitive and emotional) and left hemisphere orientated (analytic and systematic) (Remus & Kottemann, 1986). Intuition is an automatic mode of operation that allows decision makers to rapidly process information without conscious control and without being aware of this process (Dane & Prat 2007; Hodgkinson & Starbuck 2008). This decision-making model differs from the rational model in that it does not consider all the alternatives of a situation, but rather recognizes patterns, or collects clues very quickly and without any effort (Shollo, 2013). However, the ideal decision maker should balance between the two hemispheres, situation by situation (Remus & Kottemann, 1986). It is possible to make rational and independent decisions from biases with business analytics. Simon (1978) predicted that the increasing complexity of formal analysis techniques and the availability of rational approach would provide more accurate explanation of how decisions are made in organizations.

Researchers agreed on making a good decision is based on having the right data at the right time and analyzing it correctly (Remus & Kottemann, 1986). With intuition-based decision making, in the data collecting and processing stages, some biases are likely to emerge because of the human nature. In organizations, the necessary data is sometimes collected with the help of the manager's visual and auditory senses. In this stage, biases related to presenting data to a decision maker may arise. The reason that these errors persist is the neurophysiological limitations of the human brain (Remus & Kottemann, 1986). In the information processing stage, establishing the connections between each data point in the brain leads to some biases. These errors persist because of the function of the brain's organization. On the other side, with data-driven or analytical decision making, decisions are made based on the analysis of data rather than purely on intuition (Provost & Fawcett, 2013). It is an important step to build an *Analytical Decision-Making Culture* in an organization since it has many potential benefits. According to NewVantage Partners' 5^{th} annual survey of senior corporate executives on the topic of Big Data, more than 85% of participants said that they have initialized some programs to create data-driven culture within the company. However, only 37% of them succeeded, so far. According to the NVP report, the problem is not related to the technology. Failure is associated with management understanding, and general organizational resistance (Press, 2017). One of the most important discoveries of the study of Phillips et al. (1994) is the cultural effect of adopting a technology. Cultural affinity has been found to have a meaningful and positive impact on adoption through the perceived ease of (Phillips et al., 1994). If an analytical decision-making culture exists or can be built in a company, overall usefulness and ease perception related to business analytics will be affected positively. In order to test this point of view, the hypotheses 5 and 6 are developed:

Hypothesis 5: A higher level of analytical decision-making culture in an organization is associated with more perceived usefulness of the business analytics tools for the users.

Hypothesis 6: A higher level of analytical decision-making culture in an organization associated with more perceived easiness of the business analytics tools for the users.

According to Brynjolfsson, Hitt, and Kim (2011), data-driven decision making affects firm performance positively. The more data-driven the companies are the more productive they are and they have higher return on assets, return on equity, asset utilization, and market value (Provost & Fawcett, 2013).

2.3.4 Analysis Performance and, Interface and Integration Quality of the System

The first conceptual model that Davis (1985) has constructed includes system features and capabilities, users' motivation to use the system and actual system use variables. The proposed model aims to explain the motivational factors that mediate between system characteristics and user behavior, as shown in Figure 3. The features of the system affect the degree of actual use of the system by target users. Davis's research (1985) suggests that there are some motivational factors that intervene usage side. It means the features and the characteristics of the system affect how users perceive the systems, which relate to their use of the actual system.

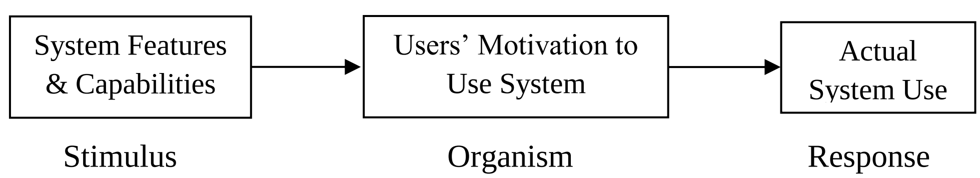

Figure 3. *Conceptual Framework* Adapted from Davis, F. D. (1985). A Technology Acceptance Model for Empirically Testing New End-User Information Systems. Massachusetts Institute of Technology.

The system or design related factors are stated as external variables in the final model of Davis (1985), as shown in the Figure 2. However, Davis (1985) did not make further investigation for external variables; instead he mainly focused on motivational factors that affect *Actual Use*. In other words, the role of external variables in TAM was not researched extensively. Davis (1993) gave a direction for the future research to take into account the role of additional (external) variables in TAM. Thus, in the present research, a variable associated with our business analytics context is examined as system related factors, namely system quality.

The construct of *System Quality* and *Information Quality* were firstly studied under the *Information Systems (IS) Success Model* proposed by DeLone and McLean (1992) who aimed to identify factors that contribute to the success of the information systems. According to this model as shown in the Figure 4, *System Quality* and *Information Quality*, individually and together, impact the use of the system and user satisfaction. *"System Quality"* indicates the performance of an IS itself, and *"Information Quality"* indicates that how qualified the output from a certain IS is (Wang & Liu, 2005). Nelson, Todd, and Wixom (2005) defined the antecedents of system and information quality constructs. According to them, while *System Quality* is composed of reliability, flexibility, accessibility, response time and integration; *Information Quality's* key dimensions are completeness, accuracy, format and currency.

Wang and Liu (2015) have studied the integration of TAM and D&M IS Success Models since they believed that both models have some weaknesses in terms of context. While TAM evaluates system usage from only users' perspective, D&M's model mixes system qualifications with the system usage, system satisfaction and further benefits of the system. They assert that by integrating the concepts of these two models as presented in Figure 5, they could possess a more comprehensive and solid model.

Wang and Liu (2005) argue that enhancing system quality and information quality supports the Perceived Usefulness and Perceived Ease of Use by increasing the overall quality of the system.

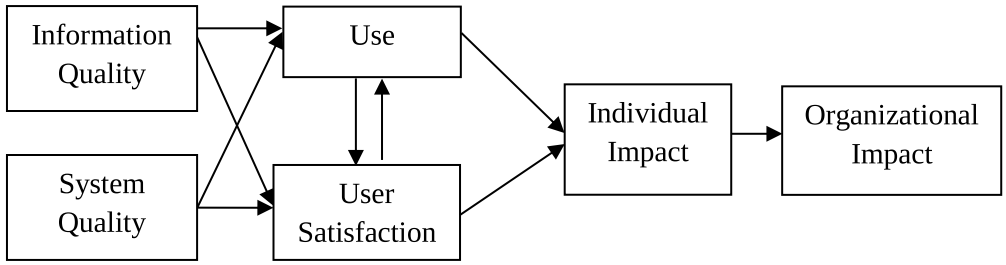

Figure 4. *The Original D&M IS Success Model* Adapted from DeLone, W. H., & McLean E. R. (1992). Information Systems Success: The Quest for the Dependent Variable. *Information Systems Research 3*(1): 60 – 95.

Boakye, McGinnis and Prybutok (2014) did not separately examine those two constructs but they proposed a full construct named "product quality" including both system quality and information quality so that they gathered quality with TAM's constructs and constructed "Q-TAM" model which indicates significant role of quality plays in acceptance and usage. Moreover, Yousafzai, Foxall, and Pallister (2007) carried out a meta-analysis of the TAM and classified all possible external variables that Davis did not mentioned in detail in his studies. They mentioned system and information quality are important factors under system characteristics that highly related with the *Perceived Usefulness* and *Perceived Ease of Use*. In addition, Kuo and Lee (2009) stated that if the quality of information is improved, *Perceived Ease of Use* will be directly influenced positively and indirectly enhanced the *Perceived Usefulness* of knowledge management systems. On the other hand, Lederer, Maupin, Sena, and Zhuang (2000) argued that information quality has the highest predictive power on *Perceived Usefulness*. Pai and Huang (2011) found that although service quality is positively related to user's *Perceived Usefulness* and *Ease of*

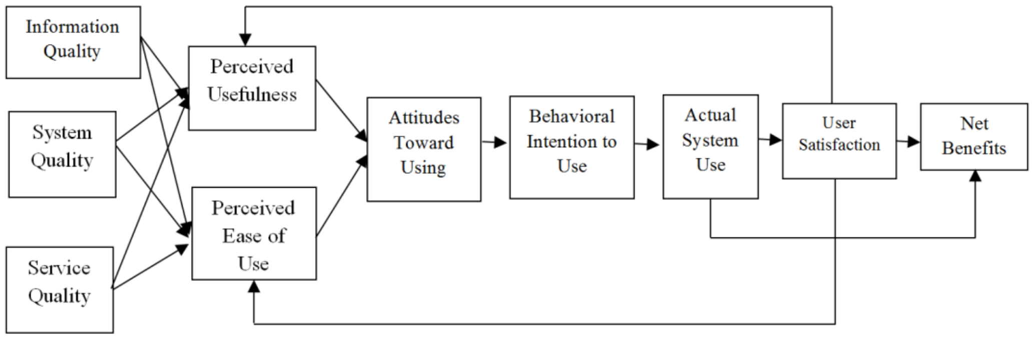

Figure 5. *The Integrated IS Success Model* Adapted from Wang W.T., & Liu C.Y. (2005). The application of the technology acceptance model: A new way to evaluate information system success. In Proceedings of the 23rd International Conference of the System Dynamics Society. Boston, MA, July.

Use, information quality is positively related to only user's *Perceived Usefulness* for healthcare information systems.

In this study, conceptually, system quality reflects the quality of interface and integration, and the information quality represents the factors that reflect the performance of the analysis provided by the system. The related determinants of Nelson et al. (2005) and additional items are selected appropriate for the present research's context and examined under two distinct construct, namely *Interface and Integration Quality of the System* and *Analysis Performance of the System*.

Davis (1993) states that although the ease of use is definitely important, the utility of the system is even more important. Users may be willing to tolerate an unpractical interface to access benefits that will help them in their job tasks (Davis, 1993). Thus, a higher interface quality leads more perceived usefulness.

According to previous strong arguments, the following four hypotheses are constituted:

Hypothesis 7: A higher analysis performance is associated with more perceived usefulness of the business analytics tools for the users.

Hypothesis 8: A higher analysis performance is associated with more perceived easiness of the business analytics tools for the users.

Hypothesis 9: A higher interface and integration quality is associated with more perceived usefulness of the business analytics tools for the users.

Hypothesis 10: A higher interface and integration quality is associated with more perceived easiness of the business analytics tools for the users.

2.4 Proposed Conceptual Model

Considering the literature review findings, a conceptual is proposed. According to the arguments, if business analytics system is high-quality in terms of many different dimensions, the user perceives that the system is useful and easy to use. Then, the attitude toward the system is positively affected. The analytical-based decision making culture positively impact attitude and use of business analytics. If users have a positive *Attitude Toward Use* the system, they are more likely to use business analytics tools in business processes. Including ten hypotheses, the conceptual model is constructed with five independent variables (*Analysis Performance of the System, Interface and Integration Quality of the System, Analytical Decision Making Culture, Perceived Usefulness* and *Perceived Ease of Use*) and two dependent variables (*Attitude Toward Use, Use of Business Analytics in Business Processes*):

Hypothesis 1: A positive attitude toward using the business analytics tools leads to a higher level of use of business analytics tools in business processes.

Hypothesis 2: If the user perceives the business analytics system as useful, a positive attitude toward the use of the system will be developed.

Hypothesis 3: If the user perceives the use of the business analytics system as easy, a positive attitude toward the use of the system will be developed.

Hypothesis 4: If the user perceives the use of the business analytics system as easy, it leads to be perceived as useful of the business analytics tools for the users.

Hypothesis 5: A higher level of analytical decision-making culture in an organization is associated with more perceived usefulness of the business analytics tools for the users.

Hypothesis 6: A higher level of analytical decision-making culture in an organization associated with more perceived easiness of the business analytics tools for the users.

Hypothesis 7: A higher analysis performance is associated with more perceived usefulness of the business analytics tools for the users.

Hypothesis 8: A higher analysis performance is associated with more perceived easiness of the business analytics tools for the users.

Hypothesis 9: A higher interface and integration quality is associated with more perceived usefulness of the business analytics tools for the users.

Hypothesis 10: A higher interface and integration quality is associated with more perceived easiness of the business analytics tools for the users.

In the light of these estimated relationships, the proposed conceptual model is stated in Figure 6.

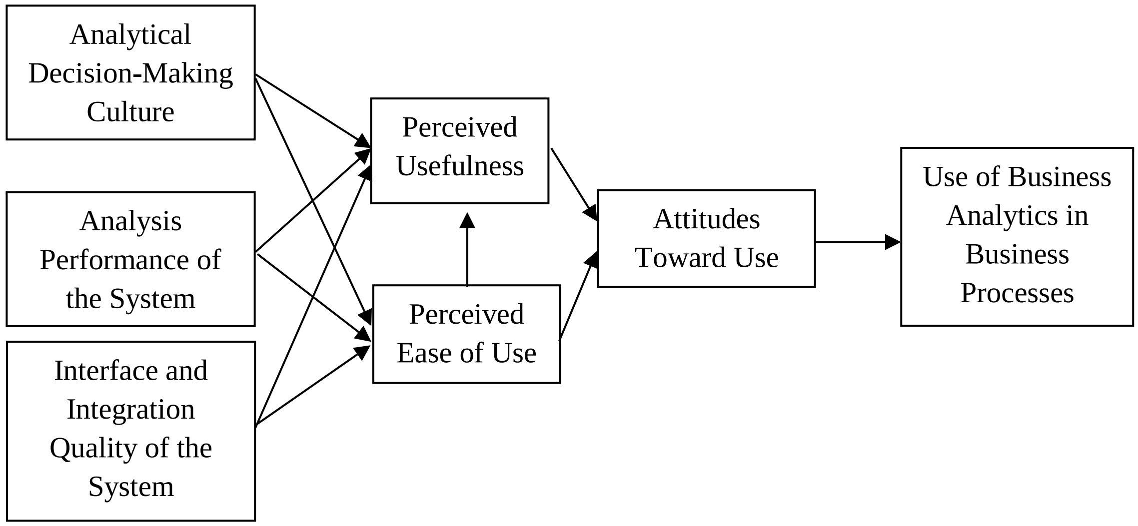

Figure 6. *Proposed Conceptual Model*

CHAPTER 3

RESEARCH METHODOLOGY

In this section, firstly research strategies and study settings are mentioned in the research approach part. Secondly, research design is stated in terms of sampling design. Finally, survey design is presented with regards to determined data collection tools and the survey questions are explained in detail.

3.1 Research Approach

The primary purpose of this research is to produce more knowledge and understanding of the issues related to the use and adaptation of the business analytics and to test an existing theory and build antecedent constructs for the theory based on the research results (Sekaran & Bougie, 2016). Thus, this research is mainly a *fundamental research*. On the other hand, it can also be considered as *applied research* due to providing practical recommendations on the use and acceptance of business analytics tools in the organizations.

In this research, there are seven constructs and ten hypotheses. The expected relationships, in other words, hypothetical arguments in the conceptual model were constructed via exploratory research and logical reasoning.

This research is a correlational study since it was conducted to identify the major factors associated with use and acceptance of business analytics tools (Sekaran & Bougie, 2016). Correlational studies are performed in non-contrived settings (Sekaran & Bougie, 2016). It is recommended that a correlational study should be carried on in a totally natural environment with minimum interference by the researcher with the normal flow of events. Thus, this study was conducted in a non-contrived setting and the researcher interference has been minimal.

In this master thesis, survey research was applied as the research strategy. A survey is used for collecting information from people to identify or compare their attitudes and behavior (Sekaran & Bougie, 2016). Since this research is mainly based on perceptions of individuals about certain systems, survey approach is most appropriate way to achieve the research objectives. Moreover, almost all of the studies based on the technology adoption model have been explored by using survey method. Hence, administering a questionnaire was selected as data collection method. Furthermore, a cross-sectional study has been carried out since this research generally demonstrates field study characteristics and has time constraints.

3.2 Research Design

In this section of the study, design of the research is explained. Firstly, unit of analysis is stated, then, sampling design is briefly discussed.

3.2.1 Unit of Analysis

Since our research question focuses on the individual level use of business analytics tool, the unit of analysis for this research is employees who use business analytics in the business processes in their organizations. The list of 15 companies was constituted and representatives from those companies were identified to be asked to participate in this study. Questionnaires were addressed to the employees estimated as having adequate knowledge of business analytics and the quality of available information for decision-making.

3.2.2 Sampling Design

In this part of the study, sampling approach is discussed. Firstly, country and industry selections are briefly explained, and then company and participant selections are clarified.

Business analytics is a fairly new topic, both for academics and for use at work place. Decision-making culture based on statistical analysis is newly formed all over the world. TAM is often used in the early or middle phase of an implementation of a system for the accurate examination of the system adaptation. Thus, it is more proper to apply this study on developing countries since these countries are beginning to invest in business analytics systems and use them in their business processes. For this purpose, as one of the biggest developing countries, Turkey was selected for data collection and analysis. In order to be able to investigate the role of business analytics in different business processes, organizations from different industries from both the public and private sector were included in the sample. Regardless of the complexity of the system they use or their level of use of the system, organizations were selected. The data were collected through a survey of 15 small, medium and large-size business organizations operating in Turkey. These organizations operate in a wide range of industries such as information technologies, finance and banking, regulating, healthcare, chemistry, foundry, petroleum, fast-moving consumer goods, energy, automotive, defense, trade (sales and marketing), service industry like human resources and brand and patent sector. Then, data were collected from employees who are using the data analysis systems for the business processes. The sizes of the target group in each organization are different and it is independent from the size of the company. A purposive sampling was chosen as a sampling method. Purposive sampling method is an effective method when the purpose and nature of the research is designed with a limited number of people (Dudovskiy, 2018). There are very few organizations that use data analysis in the business processes. Moreover, there are few employees who use these systems in this limited number of organizations. Therefore, reaching such a small and specific number of people is only possible with purposive sampling method, and more specifically expert sampling. As the name implies, expert sampling is a method which targets experts in a particular area and aims to analyze the participants in the purposive sampling (Etikan, Musa, & Alkassim, 2016). Based on these efforts, a total of 91 samples were obtained.

3.3 Survey Design

In this section of the study, the process of the preparation of the survey questions is explained in detail.

3.3.1 Survey Questions

The survey questionnaire was designed to meet the study objectives. The survey questions are direct representatives of theoretical framework.

Based on a comprehensive review of the literature in the areas of information system quality, information system acceptability and analytical decision making, survey questions were formulated. Most of the questions have been adopted from the previous researches and suggestions from academicians and practitioners (i.e. Davis, 1989; Vankatesh & Davis, 2000; Dulcic et al., 2012; Popovic, Hackney, Coelho, & Jaclic, 2012; Fathema, Shannon, & Ross, 2015; Bach, Čeljo, & Zoroja, 2016; Roca, Chiu, & Martinez, 2006; Serçemeli & Kurnaz, 2016).

The questionnaire (see Appendix A) is consisted of two parts. The first part involved multiple-choice demographic questions designed to solicit information about the system user, and the extent to which they use the analytical system. The second part involved questions related to the respondent's usage experience with the analytical system. In the second part, a five-point Likert-type scale was used ranging from "1: strongly disagree" to "5: strongly agree". For the system they use, respondents were asked to rate the *Analysis Performance* (AP) and *Interface and Integration Quality* (IIQ) associated with the business analytics tools they used, their *Perceived Ease of Use* (PEU), *Perceived Usefulness* (PU), *Attitude Toward Using* (ATU), *Actual Use of the System* (AU) and *Analytical Decision Making Culture in the Organization* (ADM). All these constructs in the proposed model are examined based on reflective multi-item scale. In this part, how all the items are constructed is briefly explained while preparing the survey questions. Based on the arguments, Table 3 which includes constructs and items of research is presented at the end of this part of the thesis.

- **Analysis Performance and, Interface and Integration Quality of the System**

In this study, general system performance and information quality aspects of a business analytics tool are examined under two constructs: *Analysis Performance of the System and, Interface and Integration Quality of the System* construct. Nelson et al. (2005) identified some dimensions in a research that they searched for system and information quality antecedence. From this study, content, response time, reliability, accuracy and format are selected as *Analysis Performance* dimensions; and, interface and integration are chosen as *Interface and Integration Quality* dimensions in line with the business analytics concept. Content of a business analytics tool is specified as the wide range of analytical functions in the system. The more functions a system offers, the more desirable the system becomes. Response time means the degree to which a system is reacting fast (Nelson et al., 2005). Hoxmeier and DiCesare (2000) argue that as system response time increases, user satisfaction decreases and in time, this dissatisfaction may lead to non-continuing use. In addition, as user satisfaction decreases, the ease of use perception of an application will decrease (Hoxmier & DiCesare, 2000). Reliability refers to the degree to which a system is performing consistently well (Nelson et al., 2005). Scientists have acknowledged that technical reliability is a factor in successful systems and they are constantly discussing some techniques for enhancing the reliability of information systems and services (Butler & Gray, 2006). Accuracy is defined as the degree of which information is correct, precise, clear, meaningful, credible, and consistent (Nelson et.al, 2005). In an analytical procedure, validation is essential to show the analytical results are suitable for its intended purpose and accuracy is considered as one of typical validation characteristics (Borman & Elder, 2017). Format is described as the degree to which information is presented to the user in an understandable and representable manner, and so that it assists in the completion of a task (Nelson et al., 2005). It is important that all results are available for download in variety of formats. DeLone and McLean (2003) described system quality measures as usability, availability, reliability, adaptability, and response time of a system, as well. Integration is identified as the degree to which a system processes by physically or functionally linking together with various sources to achieve an intended purpose (Nelson, et.al, 2005). According to Hasselbring (2000), the organizational structure and the workflows for business processes cannot be approached in isolation that means the processes of cooperating units are deeply interrelated. Hence, any interaction among computer systems reflects interactions between employees and processes; thus, it is important to consider all levels of integration between those systems to support the business processes effectively (Hasselbring, 2000). User-friendly interface of the system is determined as simple, easy-to-navigate, efficient and attractive design of the system. Ruffini (2001) argued that the design, graphics and visual elements of a system directly address to users. In line with these dimensions, McKinney, Kanghyun, and Zahedi (2002) summarize the system quality criteria as performance characteristics, functionality and usability. In this study, *Analysis Performance of the System* construct mainly measures the dimensions related to the speed, functions, features, contents, reliability, accuracy and format *and*, *Interface and Integration Quality of the System* measures the interaction capability, user-friendly interface of a system includes business analytics tools.

- **<u>Perceived Ease of Use (PEU) and Perceived Usefulness (PU)</u>**

For the constructs of usefulness and ease of use perception of a system user, the basic items determined by Davis (1989), who is the initiator of these two variables, were used. These are the well-established and frequently used items in almost every research where the technology acceptance model is studied. Serçemeli and Kurnaz (2016) used quite explanatory items while investigating the trends in the use of information technology in audit. Besides, one additional item, which was constructed by Venkatesh and Davis (2000) while develop a theoretical extension of TAM, were used in the questionnaire. These are all added to Davis' basic items. After all, within the context of *Perceived Usefulness*, it has been measured whether the system enables users to complete tasks more quickly, improve their performances, facilitate their work, provide support in important matters and increase their dominance in their work, when they use the system in their work. Within the context of *Perceived Ease of Use*, it has been measured whether the system is easy to learn to use, tasks are completed easily, the usage of the system is clear and understandable, system requires too much mental effort to use and user manuals are needed very much or not.

- **<u>Analytical Decision Making Culture in the Organization (ADM)</u>**

The major items related to *Analytical Decision-Making Culture* have been adopted from Popovic et al. (2012), where the relationship between the system maturity, information quality, analytic decision-making culture, and the use of information for decision making were examined. Participants were asked whether decisions are made primarily based on rational analytics, a decision-making process is firmly established and well-understood, their organizations pay attention to the available information regardless of the type of decision to be made and willing to use any information to be analyzed for each decision process, and managers are encouraging to handle business situations from every angle or not.

- **<u>Attitude Toward Using (ATU)</u>**

In this part of the questionnaire, participants' attitudes were measured as the last step before measuring the *Actual Use of Business Analytics* of the system. One item was selected from the research of Dulcic et al. (2012) in which they studied the use of the decision support systems. Several studies use one or two items to measure attitude (Shih, 2004). In order to prevent the problem of a single-item measure, three further items were self-constructed based on the definition of *Attitude Toward Use* discussed in the study of Fishbein and Ajzen (1975). These items were whether the participants thought it was a pleasant experience for them to use the system, whether it was a wise choice for the company to use the system, and whether they thought their organizations would reach some strategic advantage using the system.

- **Actual Use of the Business Analytics (AU)**

Finally, in order to measure the *Actual Use of Business Analytics tools*, in addition to the classic question of whether users use the system regularly or not (Dulcic et al., 2012), participants also were asked to answer how often they used the system and how much time they spent on the system within a day. In this case, since it is not allowed to view log files of each used system in order to examine log-in and log-out times or duration of use, measured self-reported usage of the systems measure was used, as is common in previous studies (e.g. Yousafzai et al., 2007). In order to balance the usage frequency and the time spent in the system, a new item was created by taking the logarithm of the product of the items of *how often they use the system* and *how much time they spend in a day while using the system*. The correlation between the items of *the situation of regularly use* and *logarithm of multiplication of how much they use the system* was found as 0.57. Moreover, the value of R^2, which illustrates how much of the variability of the *Actual Use of Business Analytics* factor can explained by its related items, has also risen. Thus, it is decided that using these two items is a reliable way to measure this construct.

- **Control Variables**

It is also constructed four control variables. Firstly, age variable was examined. Age is coded in year intervals (see Appendix A). Secondly, gender differences were tested (see Appendix A). Thirdly, the complexity level of business analytics software used was investigated. It was revealed that the participants are using more than 10 different software. These systems were divided into two groups according to the perceived complexity levels. Biewald and O'Connor (2009) divided business analytics systems into two parts: the more programming-oriented systems are R, Matlab and Python; and systems that offer more simple design are SAS, Stata and SPSS. R and Python are well-known with their complexity since they are scripting language and they have a steep learning curve. However, both R and Python are widely preferred since it offers statistical analysis in a very broad scope, and it has high versatility (NYU Data Services, n.d.). Besides, both of them are open sources. Nonetheless, functionalities of these software are limited with whether user is a good code writer or not. Although both SAS is also a programming languages, they are not even approaching R or Matlab, in terms of flexibilities. On the other hand, SPSS and Stata belong to the same category. Users, who are looking for the easiest way to do standard statistical analysis, are willing to use these systems (Biewald & O'Connor, 2009). In addition, these software's learning curves are gradual to moderate (NYU Data Services, n.d.). SAS is also widely used but, it has an outdated programming language (Biewald & O'Connor, 2009). Its learning curve is steeper than either Stata or SPSS. SAP modules where cost, profitability and quality analyzes can be conducted are known to be difficult to use as all SAP modules. Business Intelligence (BI) is a set of processes and methods that process raw data and provide meaningful and useful information transformation through analysis and decision support purposes (Pişkin, 2018). Most of the business intelligence products operate on the basis of a single-click or drag-and-drop methods and can simply create queries and reports (Bilişim AŞ, n.d.). In the light of these characteristics, the systems used by the respondents were separated into two categories: complex design and simple design. As the last control variable, the level of experience with the business analytics system they are currently using was monitored. Responses were coded into five categories: (1) Less than 1 year, (2) 1-2 years, (3) 3-4 years, (4) 5-6 years, (5) More than 6 years.

As mentioned above, in the questionnaire, many questions were asked. Table 3 illustrates all items used in the questionnaire.

3.3.2 Survey Format

The major part of the survey was completed electronically. The administration of online questionnaires was easy; and the distribution was fast (Sekaran & Bougie, 2016). Due to the time and distance constraints of this research, these factors are considered as a big advantage since it saves costs, time, and energy.

Additionally, some of the questionnaires were sent to participants via distributing the hardcopy by hand. 11% of the respondents were reached by this way. During the week of data collection, in the company where these participants work, a conference was arranged about the data analysis. At the beginning of this conference, participants were asked to give their opinions about the system they used by distributing the questionnaire. Questionnaires are personally administered by an employee in that organization. Thus, it has benefited from the advantages of personally administered questionnaires. In this way, a response rate of 100% was achieved from 18 participants.

Online questionnaires were formed as web-based. An invitation e-mail was composed with a website link, and it was sent electronically to 152 employees to complete the questionnaire. In order to increase the response rate, participants were contacted individually via phone before the invitation e-mail was sent and they were notified that they will receive an e-mail soon. Moreover, the research topic was introduced by the researcher personally in order to motivate the respondents to get correct answers. Unfortunately, online and mail surveys typically have a low response rate. Due to these efforts, out of 170 participants, 91 of them completed the questionnaire, resulting in a response rate of 53.5%.

Table 3

Survey Questions

Survey Questions		Papers Used
Analysis Performance of the System (AP)		
AP1	The speed of the system is sufficient.	Fathema, Shannon & Ross, 2015
AP2	The system content (the analysis functions presented, etc.) is quite extensive.	Fathema, Shannon & Ross, 2015
AP3	The analysis results received from the system is reliable.	Bach, Čeljo, & Zoroja, 2016; Roca, Chiu, & Martinez, 2006
AP4	I do not suffer from any data loss in the system and the system safely stores the entire information.	Self-constructed
AP5	The system provides the data in various formats according to the requests.	Roca, Chiu, & Martinez, 2006
Interface and Integration Quality of the System (IIQ)		
IIQ1	The interaction of the system with other operational systems used in my company is successful.	Fathema, Shannon & Ross, 2015
IIQ2	The system has a user-friendly interface.	Self-constructed
Perceived Usefulness (PU)		
PU1	Using the system in my job enables me to accomplish tasks more quickly.	Davis, 1989
PU2	Using the system improves my job performance.	Davis, 1989
PU3	The system makes it easier to do my job.	Davis, 1989
PU4	The system provides support for important issues at work.	Serçemeli & Kurnaz, 2016
PU5	Using the system increases my dominance at work.	Serçemeli & Kurnaz, 2016
PU6	Overall, I find the system useful in my job.	Davis, 1989

Table 3 (cont’d)

Survey Questions		**Papers Used**
Perceived Ease of Use (PEU)		
PEU1	Learning to use the system was easy for me.	Davis, 1989
PEU2	Thanks to the system, I can easily do what I want to do about work.	Davis, 1989
PEU3	Using the system is clear and understandable.	Davis, 1989
PEU4	Using the system does not require a lot of mental effort.	Vankatesh & Davis, 2000
PEU5	I do not need a user-manual when using the system.	Serçemeli & Kurnaz, 2016
PEU6	Overall, I find the system easy to use.	Davis, 1989
Analytical Decision-Making Culture (ADM)		
ADM1	In my organization, I believe that decisions are given primarily based on rational analysis.	Self-constructed
ADM2	In my organization, the data-based decision-making process is well established and known to its stakeholders.	Popovic, Hackney, Coelho & Jaclic, 2012
ADM3	It is my organization's policy to incorporate available information within any decision-making process.	Popovic, Hackney, Coelho & Jaclic, 2012
ADM4	Small or big in any decision making process, we take into account the available information.	Popovic, Hackney, Coelho & Jaclic, 2012
ADM5	In my organization, supervisor(s) encourage(s) me to consider every situation from all angles.	Self-constructed
ADM6	In my organization, supervisor(s) encourage(s) me to work detailed and methodical.	Self-constructed

Table 3 (cont'd)

Survey Questions		**Papers Used**
Attitude Toward Use (ATU)		
ATU1	Using the system is a pleasant experience for me.	Self-constructed
ATU2	I feel using the system is a wise choice.	Self-constructed
ATU3	I think that by using the system, we would achieve certain strategic advantages.	Dulcic, Pavlic, & Silic, 2012
ATU4	Overall, I have a favorable attitude towards using the system.	Self-constructed
Actual Use of Business Analytics (AU)		
AU1	I use the system regularly.	Dulcic, Pavlic, & Silic, 2012
AU2	How often do you use the system?	Self-constructed
AU3	How much time do you spend in a day directly using the system?	Self-constructed
Control Variables		
Age		
Gender		
System Complexity (Software Used)	In your business processes, which computer program do you use to analyze data?	Self-constructed
Experience	How often do you use information systems that enable to analyze data for business processes?	Self-constructed

3.3.3 Pre-testing

All required items considered to be measured were collected under the constructs and a preliminary questionnaire form was prepared. This form was pre-tested before being distributed to the participants. In pre-testing stage, it was planned to take some suggestions for correction of sentence structures or wording of the items, to control the items whether they are suitable for the purpose of the study by adding, removing or revising the necessary items related constructs. They were all discussed and finalized the questionnaire. The first pre-test was carried out with Turkey's first and the only domestic business intelligence software producer firm, Bilişim Inc. This practice was done by organizing interviews with the business intelligence product manager, business intelligence system consultants, business intelligence system test specialists and software development specialists from the company. Since they are in contact with the users every day, they have better evaluated the questions from the user perspective and their recommendations were added to the question pool created by extensive literature review. After this phase, the preliminary questionnaire form was rearranged and it was presented to an academician who is an expert in the business statistics and decision science fields. In this phase, some important adjustments were made such as eliminating some questions from the perceived usefulness construct which are asked to evaluate user's own productivity and effectiveness. It believed that these questions are not understandable and measurable and therefore cannot be answered objectively.

The final version of the survey has been constructed with the help of both an academic expert and a producer firm of business intelligence system which is the best integrated system of business analytics.

3.3.4 Ethical Considerations

Business analytics provides high value to the company and allow them to gain strategic competitive advantage in the industry. For this reason, the identity of individuals and organizations involved in the study was not asked for confidentiality.

Participants were informed of the purpose of the investigation. Confidentiality was ensured throughout the process. If any participant feels uncomfortable, they were informed that they can withdraw from any stage of the data collection process.

It is also conducted a common method bias test. Common method bias is a systematic deviation resulting from common measurement tool that change the correlations in the underlying structures by inflating or deflating (Chin, Thatcher, & Wright, 2012). It was found that there was no evidence of a common method bias according to this test. The detailed results are stated in the Section 4.4.

Besides, it is unlikely to observe a non-response bias since there was no late response to the questionnaire. For easy follow-up, questionnaire was sent to the companies on a day to day basis. The questionnaires were completed when they reached the participants or they have never replied.

Additionally, METU Applied Ethics Research Center (AERC) approved the data collection method used in the research. This center carries out an examination process in terms of basic health, safety, human rights, legal principles and universal ethical principles for the studies that researchers carry out on people or with people who are subject of a scientific research. They investigate whether the research (survey studies, laboratory experiments, field trials, interviews, reviews, etc.) are designed in a way that does not allow for a probable problem. Before the survey was conducted on participants, it was fully designed and sent to the AERC. In conclusion, it was approved that this survey does not cause any ethical concerns (see Appendix B for the Ethics Approval document).

CHAPTER 4

DATA ANALYSIS

In this chapter of the research, firstly the basic descriptive statistics are stated, then, necessary assumptions are tested. Afterwards, reliability and factor analyses are conducted, and finally predicted hypotheses are tested.

4.1 The First Glance to the Data: Descriptive Statistics

From 15 different companies, 91 business analytics system users completed the questionnaire. Table 4 illustrates the descriptive statistics. Participants from all levels of experience in using business analytics, from beginner to expert, participated in this research. Gender distribution is balanced. Generally, the sample consists of young adult workers, consisting of approximately 85% of the sample. Participants were selected from a great variety of industries, and from both private and public sectors. Of those participants, the majority are working in the private sector and specifically in the regulating and finance industry. Respondents use a wide range of business analytics systems such as business intelligence, Stata, R, and SPSS.

In univariate descriptive statistics, mainly the central tendency, dispersion (variability or spread), and shape of the distribution are examined. Regarding to the five key independent constructs, the basic descriptive statistics are exhibited in the Table 5.

Table 4

Distribution of Survey Respondents by Age, Gender, Education, Sector, Industry, Size

Age	**Frequency**	**Percentage (%)**
<30	42	46.20%
30-39	36	39.60%
40-49	11	12.10%
50-59	2	2.20%
>59	0	0.00%
Total	**91**	**100%**

Gender	**Frequency**	**Percentage (%)**
Female	45	49.50%
Male	46	50.50%
Total	**91**	**100%**

Education Level	**Frequency**	**Percentage (%)**
High school degree	0	0.00%
College/university degree	65	71.40%
Master degree	22	24.20%
Doctoral degree	4	4.40%
Total	**91**	**100%**

Sector	**Frequency**	**Percentage (%)**
Public sector	32	35.20%
Private sector	59	64.80%
Total	**91**	**100%**

Table 4 (cont'd)

Industry	**Frequency**	**Percentage (%)**
Information technologies	13	14.30%
Finance and banking	18	19.80%
Regulatory authority	18	19.80%
Healthcare	10	11.00%
Chemistry, foundry, and petroleum	11	12.10%
Fast-moving consumer goods	5	5.50%
Energy	7	7.70%
Automotive	2	2.20%
Defense	1	1.10%
Trade (sales and marketing)	3	3.30%
Service industry	2	2.20%
Other	1	1.10%
Total	**91**	**100%**

Size (Number of Employees)	**Frequency**	**Percentage (%)**
0-50	12	13.20%
51-250	16	17.60%
251-500	5	5.50%
501-1000	5	5.50%
More than 1000 employees	53	58.20%
Total	**91**	**100%**

Business Analytics System Used	**Frequency**	**Percentage (%)**
Business Intelligence (software with analytics options)	17	18.70%
R	14	15.40%
SAP (Analytical modules only)	8	8.80%
SAS	8	8.80%
SPSS	10	11.00%
Stata	24	26.40%
Other (Python, Knime etc.)	10	11.00%
Total	**91**	**100%**

Table 5

Descriptive Statistics

	Analysis Performance	Interface and Integration Quality	Perceived Usefulness	Perceived Ease of Use	Attitude Towards Use	Analytical Decision-Making Culture
Sample Size	91	91	91	91	91	91
Mean	4.025	3.341	4.082	3.090	4.021	3.823
Median	4.000	3.500	4.167	3.000	4.000	4.000
Std. Deviation	0.637	0.913	0.791	0.893	0.766	0.799
Skewness	-0.674	-0.287	-0.624	0.332	-0.708	-0.503
Kurtosis	1.202	-0.107	-0.390	-0.349	0.640	-0.255

Means of the given answers to the survey questions depict what the general tendency is. While the respondents generally find the *Analysis Performance* of business analytics tools as high-quality, they think that *Interface and Integration Quality* of the systems are perceived as medium quality. It is found that for the *Perceived Usefulness*, people rate medium-high scale answers which means users find the systems useful. As the most striking result, although respondents find the business analytics systems as high-quality and useful, they do not find it easy to use the system. Moreover, users' general attitude toward the use of these systems is positive and they also intent to use business analytics tools in the future. From the organizational point of view, the respondents feel that the *Analytical Decision-Making Culture* is moderately established in their organization.

Standard deviation measures the amount of dispersion of the data from the mean. The answers have slightly high degree of dispersion since although the responses are already in five-scale, answers differ almost one-scale it means participants have varying approaches for the same question. *Analysis Performance*, *Perceived Ease of Use* and *Attitude Toward Use* constructs seem right- skewed (mean>median), *Interface and Integration Quality*, *Perceived Usefulness* and *Analytical Decision-Making Culture* constructs seem left-skewed (mean<median).

4.2 Testing of Normality Assumption and Outlier Detection

Before starting to do a comparison test and to test constructed hypotheses, it is important to analyze the general structure of the data.

Firstly, the data were viewed to detect any possible outliers. In order to do that, histograms of each construct were monitored. As a result of this examination, no outlier observation was detected. Secondly, in order to conduct a factor analysis, and t-test, it is needed to state normality assumption. There are some different ways to test normality. In normal distribution, it is expected that the mean and median values to be close to each other. When the outputs of SPSS examined, the mean and median values for *Analytical Decision-Making Culture* and *Interface and Integration Quality* sets are not close to each other while all the remaining construct sets are relatively closer (see Table 5). As another method to recognize normality, skewness and kurtosis values are expected to be close to zero. Skewness depicts the symmetry of the distribution; zero value shows the tail balance is provided on both side of the curve. Kurtosis depicts the tailedness of the distribution; zero value indicates that the tails are not fat or thin, they are in balance. Table 5 shows that not all of the skewness and kurtosis values are close enough to zero. As another way, histograms can be visually inspected for normality assumption. Histograms of the constructs are not symmetrically bell-shaped (see Figure 7).

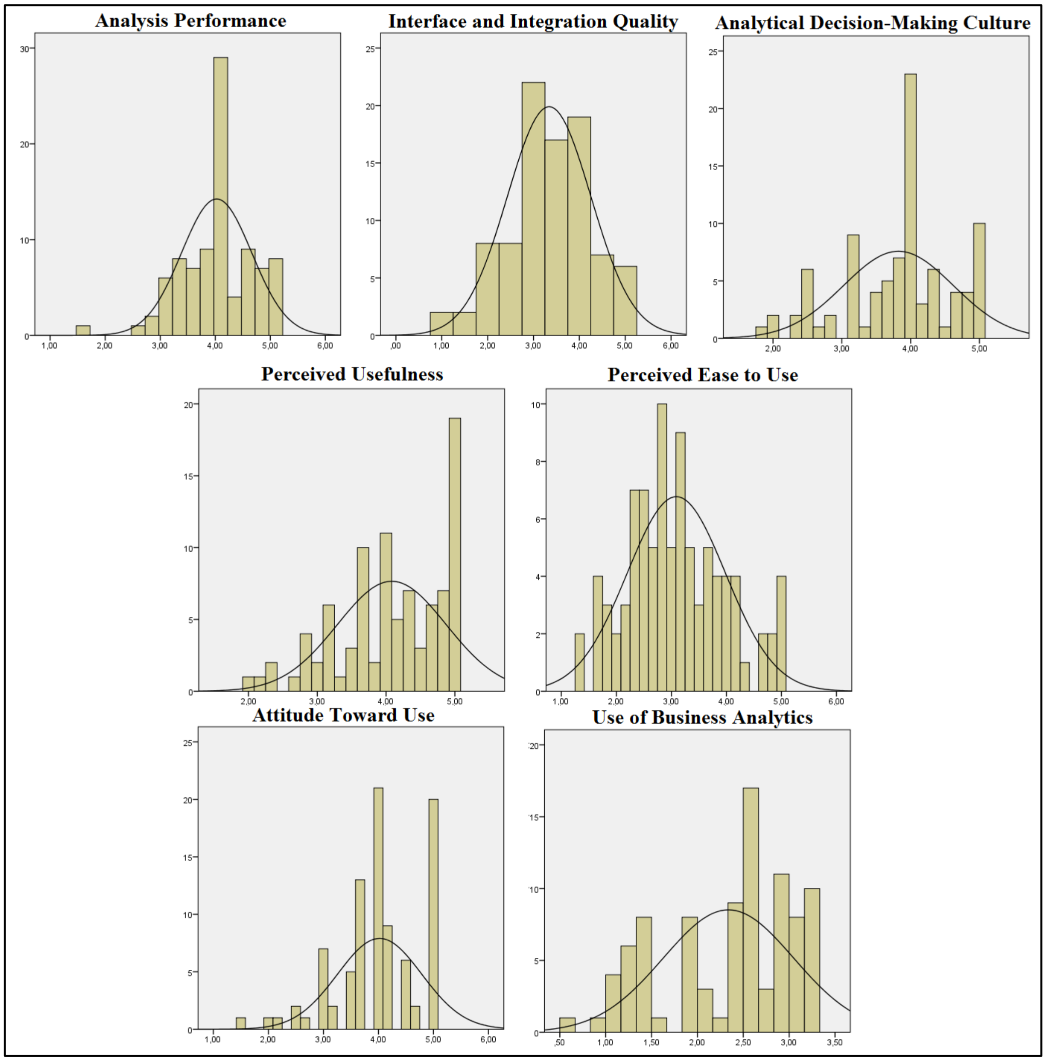

Figure 7. *Histograms of the Constructs*

In these two stages, there is no evidence to support normality assumption. As a final step, normality was checked with a formal statistical test: Kolmogrov-Smirnov and Shapiro-Wilk Tests. According to both two tests' results, it is proven that except *Perceived Ease of Use* factors, all of the constructs are not distributed normally (see Table 6).

Table 6
Tests of Normality

Constructs	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	**df**	**Sig.**	**Statistic**	**df**	**Sig.**
Analysis Performance	0.111	91	0.008	0.953	91	0.002
Interface and Integration Quality	0.135	91	0.000	0.960	91	0.007
Perceived Usefulness	0.123	91	0.002	0.920	91	0.000
Perceived Ease of Use	0.092	91	0.055	0.974	91	0.069
Attitude Towards Use	0.131	91	0.001	0.920	91	0.000
Analytical Decision Making Culture	0.148	91	0.000	0.941	91	0.000
Actual Use	0.171	91	0.000	0.902	91	0.000

4.3 The Role of Industry and System Complexity

Prior to testing the associations established in the model, some comparative tests were conducted to see whether significant differences exist in terms of all factors ultimately affecting the use of business analytics. In order to determine this, independent t-tests were applied to compare system complexity and sectoral differences and they were tested at $p<0.05$ level.

Organizations were divided into public and private sectors according to their capital structure and, production and service industries in terms of their main activities. The business analytics systems used were studied in two groups as complex and simply designed systems as described in the section 3.3.1.

The independent t-test was carried out to investigate whether there is a statistically significant difference between two sectors in terms of both capital structures and main activities; and system design complexity averages, as well. Hypotheses are stated below:

H_{A1}: $\mu_{Public\ Sector} \neq \mu_{Private\ Sector}$

H_{A2}: $\mu_{Production\ Industry} \neq \mu_{Service\ Industry}$

H_{A3}: $\mu_{Complex\ Design} \neq \mu_{Simple\ Design}$

Before conducting an independent t-test, some assumptions should be made. Firstly, the sample was randomly constituted. Secondly, the reasonably large sample size was collected ($n_{Public\ Sector}$=32, $n_{Private\ Sector}$=59, $n_{Production\ Industry}$=41, $n_{Service\ Industry}$=49, $n_{Complex\ Design}$=40, $n_{Simple\ Design}$=51). Thirdly, the data should be normally distributed. First two assumptions are valid. However, normality assumption cannot held as stated in the section 4.2. Therefore, it is necessary to state a word of caution about the validity of the results. It may not be proper to come to the sharp conclusions. Yet, stated results in the Table 7 support the final results.

SPSS presents a set of group statistics output (see Table 7) that allows the first impression before the actual comparison analysis. Means of each construct for the two groups of sectors and system types seem quite close to each other. Additionally, the homogeneity of the variance was investigated. After investigating standard deviations of each construct for the two groups, in order to statistically test equality of variances, Levene's test was conducted (see Table 8). According to the significance values, for different group comparisons, some of the constructs have p-values which are greater than 0.05, some does not have. Thus, if homogeneity of variance was validated ($Sig._{Levene\ Test}>0.05$), significance values for *Equal Variances Assumed* were analyzed while conducting t-test. Otherwise ($Sig._{Levene\ Test}<0.05$), the rest of significant values for t-test were taken into consideration. The values under consideration are indicated in bold in the Table 8.

Table 7

Differences Based on System Complexity, Capital Structure and Main Activity of Organizations, Some Basic Statistics of the Key Constructs

Construct	Complexity Level of the System	n	Mean	Std. Deviation	Sector	n	Mean	Std. Deviation	Industry	n	Mean	Std. Deviation
AP	Complex Design	40	4.263	0.572	Public	32	4.055	0.448	Production	41	3.939	0.750
	Simple Design	51	3.868	0.641	Private	59	4.034	0.726	Service	49	4.112	0.523
IIQ	Complex Design	40	3.200	1.018	Public	32	3.484	0.735	Production	41	3.341	0.897
	Simple Design	51	3.451	0.814	Private	59	3.263	0.993	Service	49	3.327	0.938
PU	Complex Design	40	4.281	0.819	Public	32	4.109	0.657	Production	41	4.043	0.873
	Simple Design	51	3.956	0.748	Private	59	4.093	0.862	Service	49	4.128	0.722
PEU	Complex Design	40	3.146	0.974	Public	32	2.917	0.680	Production	41	3.215	0.953
	Simple Design	51	3.046	0.832	Private	59	3.184	0.983	Service	49	2.963	0.828

Table 7 (cont'd)

Construct	Complexity Level of the System	n	Mean	Std. Deviation	Sector	n	Mean	Std. Deviation	Industry	n	Mean	Std. Deviation
ATU	Complex Design	40	4.181	0.749	Public	32	4.076	0.500	Production	41	3.915	0.928
	Simple Design	51	3.895	0.762	Private	59	3.992	0.880	Service	49	4.100	0.600
ADM	Complex Design	40	3.954	0.849	Public	32	3.850	0.642	Production	41	3.817	0.846
	Simple Design	51	3.720	0.749	Private	59	3.808	0.877	Service	49	3.824	0.774
AU	Complex Design	40	2.636	0.584	Public	32	2.053	0.722	Production	41	2.477	0.639
	Simple Design	51	2.105	0.718	Private	59	2.494	0.660	Service	49	2.206	0.747

Table 8

Comparison Results

Construct	Homogeneity of Variance	Independent Samples t-test for System Complexity				Independent Samples t-test for Capital Structure of Organizations				Independent Samples t-test for Main Activity of Organizations			
		Levene's Test for Equality of Variances		t-test for Equality of Means		Levene's Test for Equality of Variances		t-test for Equality of Means		Levene's Test for Equality of Variances		t-test for Equality of Means	
		F	Sig.	t	Sig. (2-tailed)	F	Sig.	t	Sig. (2-tailed)	F	Sig.	t	Sig. (2-tailed)
AP	Equal variances assumed	0.313	0.577	3.057	**0.003**	6.246	0.014	0.147	0.883	3.725	0.057	-1.287	**0.202**
	Equal variances not assumed			3.100	0.003			0.169	**0.866**			-1.247	0.216
IIQ	Equal variances assumed	2.230	0.139	-1.307	**0.194**	5.318	0.023	1.108	0.271	0.010	0.920	0.077	**0.939**
	Equal variances not assumed			-1.273	0.207			1.210	**0.230**			0.077	0.939

Table 8 (cont'd)

		Independent Samples t-test for System Complexity				Independent Samples t-test for Capital Structure of Organizations				Independent Samples t-test for Main Activity of Organizations			
Construct	**Homogeneity of Variance**	**Levene's Test for Equality of Variances**		**t-test for Equality of Means**		**Levene's Test for Equality of Variances**		**t-test for Equality of Means**		**Levene's Test for Equality of Variances**		**t-test for Equality of Means**	
		F	**Sig.**	**t**	**Sig. (2-tailed)**	**F**	**Sig.**	**t**	**Sig. (2-tailed)**	**F**	**Sig.**	**t**	**Sig. (2-tailed)**
PU	Equal variances assumed	0.898	0.346	1.976	**0.051**	4.244	0.042	0.092	0.927	2.234	0.139	-0.505	**0.615**
	Equal variances not assumed			1.954	0.054			0.100	**0.921**			-0.496	0.621
PEU	Equal variances assumed	0.967	0.328	0.528	**0.599**	7.340	0.008	-1.367	0.175	2.304	0.133	1.347	**0.182**
	Equal variances not assumed			0.518	0.606			-1.520	**0.132**			1.330	0.187

Table 8 (cont'd)

Construct	Homogeneity of Variance	Independent Samples t-test for System Complexity				Independent Samples t-test for Capital Structure of Organizations				Independent Samples t-test for Main Activity of Organizations			
		Levene's Test for Equality of Variances		t-test for Equality of Means		Levene's Test for Equality of Variances		t-test for Equality of Means		Levene's Test for Equality of Variances		t-test for Equality of Means	
		F	Sig.	t	Sig. (2-tailed)	F	Sig.	t	Sig. (2-tailed)	F	Sig.	t	Sig. (2-tailed)
ATU	Equal variances assumed	0.000	0.986	1.789	**0.077**	7.997	0.006	0.498	0.620	6.699	0.011	-1.144	0.256
	Equal variances not assumed			1.793	0.077			0.581	**0.563**			-1.103	**0.274**
ADM	Equal variances assumed	0.618	0.434	1.398	**0.166**	5.855	0.018	0.239	0.812	.910	0.343	-0.039	**0.969**
	Equal variances not assumed			1.377	0.172			0.262	**0.794**			-0.039	0.969

Table 8 (cont'd)

Construct	Homogeneity of Variance	Independent Samples t-test for System Complexity				Independent Samples t-test for Capital Structure of Organizations				Independent Samples t-test for Main Activity of Organizations			
		Levene's Test for Equality of Variances		t-test for Equality of Means		Levene's Test for Equality of Variances		t-test for Equality of Means		Levene's Test for Equality of Variances		t-test for Equality of Means	
		F	Sig.	t	Sig. (2-tailed)	F	Sig.	t	Sig. (2-tailed)	F	Sig.	t	Sig. (2-tailed)
AU	Equal variances assumed	9.069	0.003	3.794	0.000	3.064	0.083	-2.948	**0.004**	4.252	0.042	1.825	0.071
	Equal variances not assumed			3.889	**0.000**			-2.870	0.006			1.851	**0.068**

In order to interpret the results of the t-test for the difference in the two means, the p-values for the each construct were evaluated. In terms of system complexity, as shown in the table 8, the significance values of the constructs except *Analysis Performance* and *Actual Use* constructs are all greater than 0.05 implying that, at different levels of complexity, only analysis performance perception and the level of business analytics use quite differ. It means with a more complex business analytics system, analysis performance is perceived as higher and the level of use is higher, as well. According to sectoral comparison in terms of capital structure, only the level of use of business analytics is different between public and private sectors. Employees who are working at private sector are using business analytics systems more intensively ($Mean_{Private\ Sector}=2.494 > Mean_{Public\ Sector}=2.053$). On the other side, perspective on the entire constructs does not vary for production and service industries. Results indicate that, overall, the level of use of business analytics is affected both by the degree of difficulty of the system and by the capital structure. It is found that in case of higher system complexity, the level of use of business analytics is higher ($Mean_{Complex\ Desing}=2.636 > Mean_{Simple\ Design}=2.105$). Moreover, evaluation of the analysis performance is highly affected by the degree of complexity of the business analytics system. It is stated that with higher system complexity, analysis performance is evaluated in a higher level ($Mean_{Complex\ Desing}=4.263 > Mean_{Simple\ Design}=3.868$). However, the differences in the main activities of the organizations do not make any difference on any constructs that is being investigated.

4.4 Structural Equation Modeling (SEM) and Partial Least Squares Method (PLS)

Social sciences, especially business research, usually investigate complicated relationships most of the time, since studies include social and psychological contexts (Bowen & Guo, 2012). In order to analyze these complicated relationships, traditional regression analysis can be conducted to forecast change in a dependent variable on a model on the basis of change in independent variables, under the normality assumption. However, in this study, it is not proper to test all the hypotheses with any parametric method like a multiple linear regression technique since the constructed model has complex relationships and data is not distributed normally.

Structural equation modeling (SEM) is a general statistical approach that executes more than one predicted and predictor variables simultaneously (Bowen & Guo, 2012). SEM explores the relational situations in path diagram (Bowen & Guo, 2012). Latent variables form the center of these path diagrams. This type of variables reflects social, organizational and psychological cases such as perceptions, emotions, attitudes, characteristics explained with multiple items (Bowen & Guo, 2012). It is also called unobserved variables which means indirectly refer to the observed variables that are written in the datasheets. SEM is specialized in easily identifying casual relationships among latent variables including moderation relationships, contrary to the regression methods which analyze the observed variables. Moreover, SEM is able to test reliability and validity successfully (Bowen & Guo, 2012).

As a well-known method under SEM, the partial least squares path modeling (PLS) technique permits analyzing complex relationships between latent variables. PLS relies on a nonparametric bootstrap method that makes possible to reach conclusions for which both while normality assumption is not held and there is a small sample size since it randomly creates subsamples from the original data set and it continues until a large number of random subsamples are generated (Chin, 1998).

To conclude, PLS method was selected to do relational analyses in constructed model. Thus, in this research, model analysis was completed with a PLS-specific software: SmartPLS 3.0. There are two stages of the PLS analysis:

1) Testing the reliability and validity of the measurement model
2) Finalizing the structural model

In the next two sections, the two steps will be performed.

4.5 Measurement Model

The conceptual model is set up with seven constructs which includes multiple items in each of them. In this research, survey questions are prepared as one-to-five scale, and scales are constructed as reflective-based which means items share a common basis and they are expected to be correlated. In a nutshell, they are reflecting what they are measuring for (Sekaran & Bougie, 2016).

In PLS, before testing hypotheses, construct reliability and validity should be examined.

Reliability analysis examines the consistency of the study by analyzing the scale of measurement within a single unidimensional construct (Sekaran & Bougie, 2016). It investigates whether the items belong to one another as a set within the single construct. In short, the reliability analysis examines whether the items are measuring the same underlying phenomenon. Main measurements of construct reliability are Cronbach’s alpha and composite reliability. Factor analysis examines item relationships as a whole (Sekaran & Bougie, 2016). Convergent validity is controlled with the average variance extracted (AVE) which is expected to be greater than 0.5 for the construct level and item loadings are expected to be greater than 0.7 at the item level (Peng & Lai, 2012). Discriminant validity is tested by comparing the square root of AVE with the correlations between constructs. For each construct, the square root of AVE is expected to be greater than correlations between the focal construct and all other constructs (Fornell & Larcker 1981). Apart from these widely accepted standard procedures, formative and reflective constructs are treated differently. It is reasonable to apply both reliability and factor analyzes on reflective constructs. Internal consistency is not a proper validation criterion for formative indicators since formative indicators need not be highly correlated. Hence, since all of the constructs are set up as reflective in nature, the reliability and factor analysis are carried out for all the constructs.

As a starting step, all seven construct sets with all items are executed together on the analysis in the SPSS. According to the factor loading values, in *Analysis Performance* construct, the item AP5 seems problematic. It is desired that one item should be highly associated with only a single factor. However, AP5 is explaining 51.5% of the variance of the first factor, but also explaining 50.5% of the variance of the second factor. It means AP5 is not a distinguishable item enough. Thus, the item AP5 was extracted from the analysis. Hence, the further analysis was continued with seven constructs and the remaining items using SmartPLS 3.0 software under the PLS method.

According to the reliability analysis results in the table 9, for the *Perceived Usefulness, Perceived Ease of Use, Analytical Decision-Making Culture, Analysis Performance of the System, Interface and Integration Quality of the System, Attitude Toward Use,* and *Actual Use of Business Analytics* sets, the

Cronbach's Alpha values are all found as greater than 0.7 and they verify the reliability of each construct in itself. In addition, inner variance inflation factor (VIF) is used to detect multicollinearities between the constructs. VIF is recommended to be lower than 5 (Hair, Ringle, & Sarstedt, 2011). Fortunately, the inner VIF values of all constructs are all less than 2.

As the second step of the analysis, in terms of convergent validity, all of the average variance extracted (AVE) values are greater than 0.5 for the each construct (Peng & Lai, 2012). However, since the correlation between *Attitude Toward Use* and *Perceived Usefulness* is high, discriminant validity could be compromised (see Table 13 in the Appendix C). The square root of AVE is expected to be greater than correlations between the focal construct and all other constructs, by respectively a wide margin. Therefore, only the items of PU1, PU4, PU5 and PU6 were used for analysis. It is determined that these items are more conceptually related to business analytics since these are explanatory items of the use of business analytics to decision support mechanism in job tasks, while PU2 and PU3 are measuring job performance rather than usefulness. By extracting PU2 and PU3 items from the *Perceived Usefulness* construct, the discriminant validity result was improved. It was continued with all the remaining items to the study.

A final reliability and validity analysis were carried out with the newly created constructs and extracted items. Reliability measures perfectly fit. Cronbach's Alpha and composite reliability results are highly satisfactory (see Table 9). Validity measures are quite acceptable. Considering convergent validity, except the item AP4, all of the factor loadings are over 0.7 which is usually accepted as the threshold level. The loading of this item is very close to the cut-off value (0.68), and taking the content validity of the latent construct into consideration, AP5 is retained (see Table 9). Moreover, AVE values are well above the recommended minimum of 0.5 (see Table 9). Besides, correlation analysis was conducted. It simultaneously analyzes two variables to test whether there is a relationship between the variables or not. It is basically a pre-step before the conducting relationship analyses as a first look to the possible linear relationship between the constructs. A value of ± 1 shows a perfect linear association between the variables. The linear relationship is getting weaker as the correlation coefficient value gets closer 0 (Sekaran & Bougie, 2016). As stated in the Table 10, firstly, all of the relations are found as statistically significant, it proves the linear relationship between the constructs. It is also displayed that discriminant validity is attained. The square roots of AVE values of each latent construct are higher than the construct's highest correlation with any other latent construct.

Finally, some tests were conducted to analyze common method bias. In PLS-SEM context, common method bias is a systematic error that is caused by the measurement method used in the study (Kock, 2015). According to Kock's (2015) suggestion, in the light of the full collinearity test, if all of the VIF's are equal to or lower than 3.3, the model might be considered free of common method bias. In addition to that, Harman's (1960) single factor test was executed to traditionally test the presence of common method bias. All items are forced to examine under one factor in factor analysis. If a single factor constitutes the majority of the covariance between variables, the existence of a common method variance can be shown (Podsakoff, MacKenzie, & Podsakoff, 2003). According to the result of exploratory principal components factor analysis, it is observed that the 46% of the variance explained by the single factor which is below the commonly accepted threshold of 50% (Harman, 1960). Therefore, it can be concluded that this study does not suffer from common method bias.

Table 9

Measurement Properties of the Constructs

Construct	Item Indicator	Item Loading	T-Stat.	Cronbach's Alpha	Composite Reliability	Communality (AVE)
Analysis Performance of the System	AP1	0.842	15.501	0.782	0.859	0.607
	AP2	0.741	9.699			
	AP3	0.846	20.216			
	AP4	0.673	10.648			
Interface and Integration Quality of the System	IIQ1	0.876	29.805	0.724	0.879	0.783
	IIQ2	0.894	37.110			
Analytical Decision-Making Culture	ADM1	0.888	38.827	0.943	0.955	0.779
	ADM2	0.947	76.462			
	ADM3	0.905	42.911			
	ADM4	0.840	18.387			
	ADM5	0.902	29.546			
	ADM6	0.805	17.027			

Table 9 (cont'd)

Construct	**Item Indicator**	**Item Loading**	**T-Stat.**	**Cronbach's Alpha**	**Composite Reliability**	**Communality (AVE)**
Perceived Usefulness	PU1	0.887	46.285	0.907	0.935	0.781
	PU4	0.874	31.769			
	PU5	0.865	23.693			
	PU6	0.909	32.815			
Perceived Ease of Use	PEU1	0.807	15.328	0.889	0.914	0.641
	PEU2	0.734	12.519			
	PEU3	0.862	17.490			
	PEU4	0.730	10.118			
	PEU5	0.805	17.354			
	PEU6	0.857	28.984			
Attitude Toward Use	ATU1	0.879	26.159	0.908	0.936	0.785
	ATU2	0.900	34.174			
	ATU3	0.848	22.735			
	ATU4	0.916	46.043			
Actual Use of Business Analytics	AU1	0.906	39.960	0.727	0.879	0.784
	log(AU2*AU3)	0.864	13.297			

Table 10

Correlations between the Latent Variables and Square Roots of the Average Variance Extracted

	Actual Use of Business Analytics	Analysis Performance of the System	Analytical Decision-Making Culture	Attitude Toward Use	Interface and Integration Quality of the System	Perceived Ease of Use	Perceived Usefulness
Actual Use of Business Analytics	**0.886**						
Analysis Performance of the System	0.459	**0.779**					
Analytical Decision-Making Culture	0.321	0.337	**0.882**				
Attitude Toward Use	0.529	0.705	0.553	**0.886**			
Interface and Integration Quality of the System	0.299	0.415	0.489	0.556	**0.885**		
Perceived Ease of Use	0.505	0.354	0.485	0.627	0.601	**0.801**	
Perceived Usefulness	0.591	0.648	0.600	0.816	0.613	0.605	**0.884**

Note. The square root of average variance extracted (AVE) is presented on the diagonal of the correlation matrix and inter-construct correlations are presented off the diagonal.

4.6 Final Model Construction

In order to test relationship between the constructs in the structural model (see Figure 8), the bootstrap resampling method was conducted. In the bootstrapping procedure, in the literature, the high numbers of bootstrap samples are suggested. For instance, Chin (1998) recommends 500 resampling. With the increasing computation power of software today, even more bootstrapping samples are recommended (>500). It enables reducing the effect of random sampling errors (Peng & Lai, 2012). Hence, resampling size was chosen as 500.

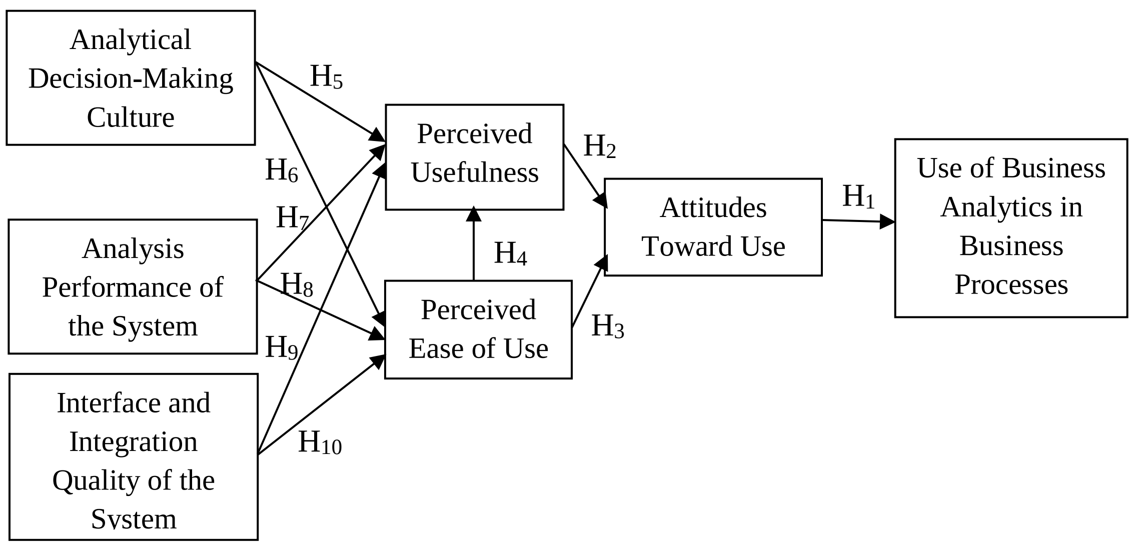

Figure 8. *Proposed Conceptual Model*

The results of the analysis with the direct effects between the constructs are stated in Table 11 and visually, in Figure 9. In addition to this, in Figures 11 and 12 (see Appendix D), there are also graphical representations of PLS method result. As it was expected, except one hypothesis, the entire hypotheses are supported. A positive attitude toward using the business analytics tools was found to be positively associated with the use of business analytics tools in the business processes, (ϒ= 0.529, p=0.000) supporting (in Hypothesis 1). In addition, if the user perceives the business analytics system as useful and easy to use, they develop a positive attitude toward the use of the system, (ϒ= 0.688, p=0.000; ϒ= 0.211, p=0.009) supporting (in Hypothesis 2 and 3, respectively). Furthermore, when the user perceives the use of the business analytics system as easy, it leads to be perceived as useful, as well, (ϒ= 0.224, p=0.002) supporting (in Hypothesis 4).

When the antecedent factors are examined, existence of analytical decision-making culture in an organization leads to be perceived as both useful and easy of the business analytics tools for the users, (ϒ= 0.267, p=0.000; ϒ= 0.236, p=0.024) supporting (in Hypothesis 5 and 6, respectively). On the other hand, if the integration and interface quality of the system they used is high, employees perceive the business analytics tool as easy and useful, (ϒ= 0.180, p=0.041; ϒ=0.449, p=0.000) supporting (in Hypothesis 9 and 10, respectively). However, while a higher analysis performance of a business analytics tool leads to be perceived as useful, (ϒ=0.404, p=0.000) supporting (in Hypothesis 7), no significant direct effect exist between high analysis performance and easy perception, (ϒ=0.088, p=0.252) supporting (in Hypothesis 8).

As two final steps, firstly, to evaluate the predictive power of the constructed model, the explained variance (R^2) of the endogenous variables should be examined and then, overall model fit statistics should be investigated carefully (Peng & Lai, 2012). In terms of the explained variance (R^2), the structural model has highly satisfactory results (see Table 12) since R^2 values of the endogenous variables are in the range between substantial and moderate level ($R^2_{\text{Actual Use}}$=0.280, $R^2_{\text{Attitude Towards Use}}$=0.694, $R^2_{\text{Perceived Usefulness}}$=0.668, $R^2_{\text{Perceived Ease of Use}}$=0.415) (Peng & Lai, 2012).

Considering the model fit, a highly accepted goodness-of-fit formula stated by Tenenhaus, Vinzi, Chatelin, and Lauro (2005) was used. This formula is basically based on AVE and R^2 values. It is computed by taking the square root of the product of the average R^2 value of the endogenous variables and the average communality of all constructs. For our structured model, fitting result is 0.616 (see Table 12), which is quite above the accepted cut-off value of 0.36 stated by Fornell and Larcker (1981). Furthermore, in order to ensure the adequacy of sample the G*Power 3 software is used to conduct a kind of power analysis and F-test, as suggested by J. Cohen, P. Cohen, West, and Aiken (1983). Using the R^2 value (0.28) of the ultimate dependent variable *Actual Use*, a Cohen's f^2 method of effect size was calculated (f^2=0.38) and assuming a significance level (α) of 0.05 and a desired power (1-β) of 0.95 with 6 predictors, the analysis would require a sample size of 62. In this research, it is exceeded this threshold with actual sample size of 91.

In order to execute robustness check, a model with control variables of *Age, Gender, System Complexity* and *Experience Level with Business Analytics Use in Business Processes,* was tested. It was found that *Age* and *Gender* have no significant effect on the *Actual Use of Business Analytics* (t=0.548 and t=0.256, respectively). However, *Experience Level* and *System Complexity* is quite effective on the use of these kinds of systems (t=2.032 and t=2.303, respectively). In the analysis performed with the control variables, entire path coefficients and significance values were found almost identical to the coefficients estimated in the model without controls (see Figure 11 and Figure 13 in the Appendix D). Furthermore, adding a control variable has increased the explanatory power of the model by approximately 11% (see Figure 10 and Figure 12 in the Appendix D).

Table 11

Structural Estimates with Hypothesized Relationships

Hypothesis	**Path**	**Path Coefficient**	**T-Stat**	**95% Confidence Interval**	**p-value**	**Result**
H_1	Attitude Toward Use → Actual Use (+)	0.529	5.368	(0.332, 0.704)	0.000	Supported
H_2	Perceived Usefulness → Attitude Toward Use (+)	0.688	9.239	(0.518, 0.814)	0.000	Supported
H_3	Perceived Ease of Use → Attitude Toward Use (+)	0.211	2.628	(0.078, 0.398)	0.009	Supported
H_4	Perceived Ease of Use → Perceived Usefulness (+)	0.224	3.160	(0.094, 0.371)	0.002	Supported
H_5	Analytical Decision Making Culture → Perceived Usefulness (+)	0.267	3.569	(0.105, 0.396)	0.000	Supported
H_6	Analytical Decision Making Culture → Perceived Ease of Use (+)	0.236	2.260	(0.032, 0.435)	0.024	Supported
H_7	Analysis Performance of the System → Perceived Usefulness (+)	0.404	6.052	(0.290, 0.544)	0.000	Supported
H_8	Analysis Performance of the System → Perceived Ease of Use (+)	0.088	1.147	(-0.073, 0.247)	0.252	Not Supported
H_9	Interface and Integration Quality of the System → Perceived Usefulness (+)	0.180	2.054	(-0.003, 0.337)	0.041	Supported
H_{10}	Interface and Integration Quality of the System → Perceived Ease of Use (+)	0.449	4.394	(0.232, 0.632)	0.000	Supported

Table 12

R^2, Communality, and Goodness of Fit

	Actual Use of Business Analytics	**Attitude Towards Use**	**Perceived Ease of Use**	**Perceived Usefulness**	**Analytical Decision Making Culture**	**Analysis Performance of the System**	**Interface and Integration Quality**	**Average**
R^2	0.280	0.694	0.415	0.668				0.51425
Communality (AVE)	0.784	0.785	0.641	0.781	0.779	0.607	0.783	0.73714
Goodness of Fit								**0.616**

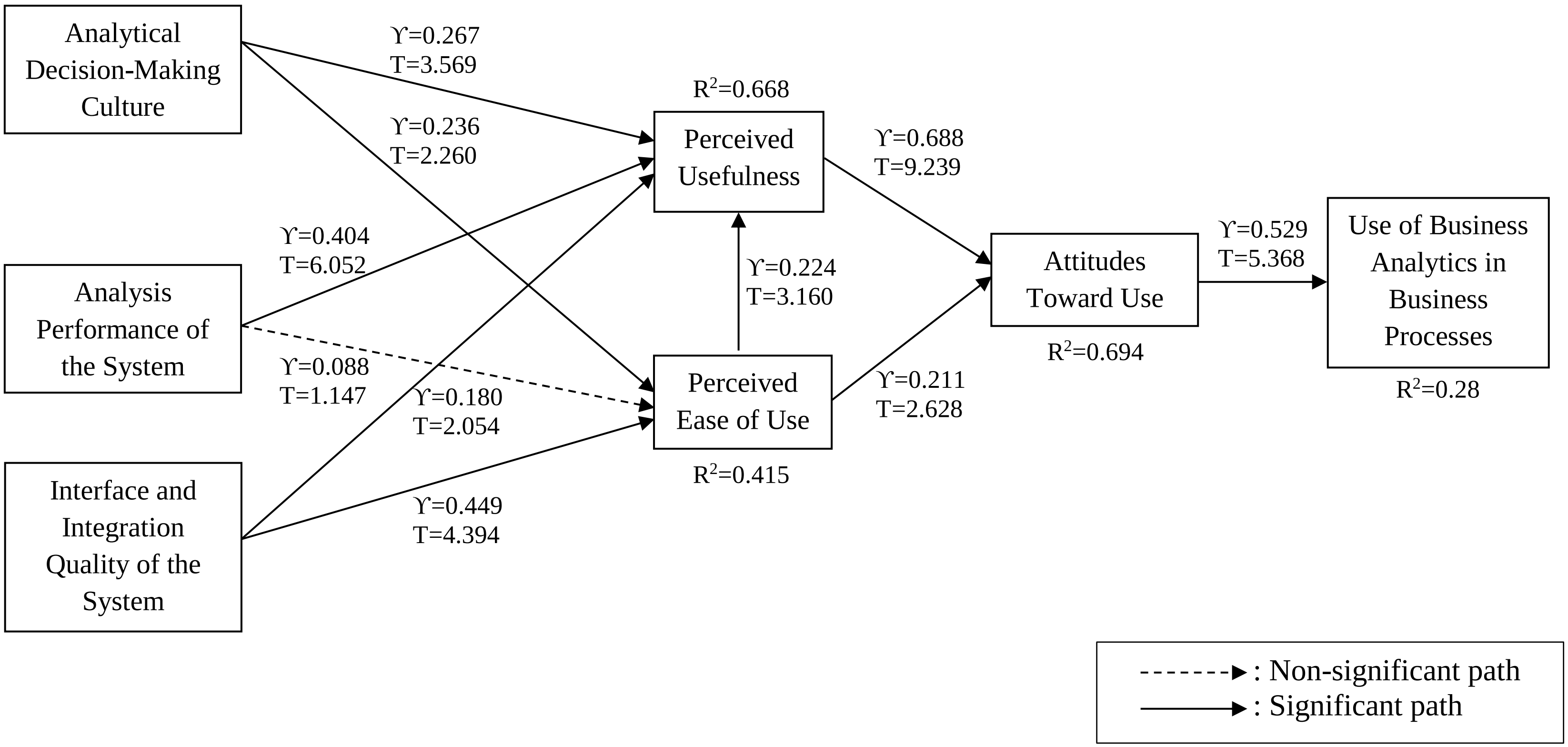

Figure 9. *Structural Model*

CHAPTER 5

CONCLUSIONS

In this chapter of the research, first findings of the study are stated as an extensive summary, then, theoretical and practical contributions are depicted, and finally limitations are indicated and recommendations are given for future research.

5.1 Findings

In this master thesis, TAM is extended through the addition of three important antecedents: *Analytical Decision-Making Culture in the Organizations, Analysis Performance of the System* and *Interface and Integration Quality of the System* constructs. The extended TAM model is tested in the context of business analytics systems. This study contributes to both academia and practice by handling a hot topic: *Business Analytics* which turns data into actionable insights in organizations. Second, the study makes contribution with one significant organizational factor: *Analytical Decision-Making Culture in Organizations* which is an enterprise-wide commitment to data and analytics. Organizations with analytical decision-making culture see coming problems and take preventions rather than being reactive, always transmit reliable and timely information to take right and quick actions, develop a culture of fact-based decision making through all functions and all levels of the organization and build an analytic culture where analysis is the base of corporate DNA. In short, they set their business strategies based on what the analytics tell them (McGuire & Rose, n.d.). Third, this research contributes with two substantial technological factors: *Analysis Performance of the System* and *Interface and Integration Quality of the System. Analysis Performance of the System* reflects the speed of completion of an analysis and displaying on the screen, variedness of analysis presented to the user, and the reliability of the analysis results. *Interface and Integration Quality of the System* indicates having a user-friendly interface and the success of the system while integrating with other operational systems in the organization. Their impacts on perceptions are different. While analysis performance affects perceived usefulness, interface and integration quality impacts perceived ease of use at a high rate. In addition, interface and integration quality slightly affects the perceived usefulness. Four, the study successfully tested the basic variables of the technology acceptance model which are *Perceived Usefulness, Perceived Ease of Use, Attitude Toward Use, and Actual Use*. In this way, the study investigates an existing, but expanding IS theory in a new IT context.

The process of accepting and using technology of individual users is a complicated process that cannot be explained with few variables. There are many variables that contribute to the clarification of user's usage of the technology. Therefore, all relevant details should be examined from a wide perspective, from the characteristics of the technology being explored and, the characteristics of the organization to the characteristics of the users who are using the technology (Dillon, 2001).

First of all, it would be better to start examining the link between antecedents and perception factors. In terms of system quality dimensions, primarily, the analysis performance factor is examined. Analysis performance is the key for meeting users' requirements (Saha, Nath, & Salehi-Sangari, 2012). Subheadings of analysis performance of a business analytics system include the speed of analysis, the variety and content of analysis functions, the reliability of the analysis results and the safe storage of the data. These subbranches were examined sequentially. First of all, human is impatient by their nature. Slow response times can frustrate users to analytical use. Organizations put a variety of performance-enhancing efforts to handle poor performance problems. Faster performance showing analysis results, and reports eventually increases overall positive attitude and usage (Mansell, 2015). Reliability of retrieved information is important since reports are useless if output has poor quality. Garbage in causes garbage out. Accurate information is more beneficial and thus the more valuable (Venkatesh & Bala, 2008). Besides, safely storage without any data loss is a crucial element in system quality design. If all quality indicators are met adequately, users perceive the system as useful and use of the analysis will increase. On the other side, user's perspective is opposite in terms of perception for easy to use. It is speculated that a perception is constituted that a good analysis performance complicates the system. Complexity is closely related to the degree of sophistication of the content and how an individual perceives difficulty while using the system. Users will embrace the system if it is easy to use and if using of the system makes it easier to decide within the organization (Grubljesic & Jaklic, 2015). It also proves if the user perceives the use of the business analytics system as easy, a positive attitude toward the use of the system will be developed. To conclude, a solid analytical performance improves user's perception as useful, but not as easy to use. On the other hand, an interface completes the overall system quality of the system. A user-friendly interface is expected to be well organized, simply designed, visually appealing, and quickly and easily accessible to every part of the system. It leads the system will be easy to learn and easy to use. Interestingly, it also leads to be perceived as useful for the users. All of these factors will provide a situation in which users are willing to and continue to use business analytics tools (Saha et al., 2012). Integration expresses compatibility of the business analytics system with other source systems, both inside and outside the organization. This enables information aggregation from other operational systems and enriches reporting and analysis capability within the organization (Karahanna et al., 1999). As a result, a higher interface and integration quality of the system leads to be perceived as useful and easy of the business analytics tools for the users.

It is further illustrated that analytical decision-making culture, is an important organizational factor as an antecedent of TAM. Decision-makers' choice of using information and analytics is highly influenced by presence of analytical decision-making culture in the organization (Elam & Leidner, 1995; Singh, Watson, & Watson, 2002). The results show that analytical decision-making culture positively impacts both perceived usefulness and perceived ease to use. Once organizations have reached higher levels of analytical decision-making culture, decision makers tend to use existing information, regardless of the quality of the system since they believed that the system is useful and also easy to use (Popovic et al., 2012). In conclusion, if an analytical decision-making culture exists in an organization, the business analytics users perceived the business analytics system as useful and easy.

Considering the basic variables of TAM, perceived usefulness and perceived ease to use is investigated. The extent to which people require information to complete their job tasks and add value to the business by doing more than necessary is utilizing analytics (Grubljesic & Jaklic, 2015). Usefulness perception such as relative advantage, job relevance, accomplishing tasks more quickly, providing support for important issues, increases the dominance at work and briefly, supporting the decision support mechanism are significantly positively impacts the attitude toward analytics usage. As previously mentioned, the complexity issue significantly impacts perceived ease to use on attitude toward use. However, as Davis (1986) also stated, perceived usefulness has a much stronger effect on attitude toward use the system than perceived ease to use. Moreover, as demonstrated in Davis' first study (1986) and further many technology acceptance model test research, if the user perceives the use of the business analytics system as easy, it leads to be perceived as useful of the business analytics tools for the users, as well. The relationship between perceived ease to use and usefulness is always found interesting. Although the explanation is still not clear, Davis (1989) states that while other factors are kept equal, with easier interaction with a system, less effort to operate it, and much of the contributions can allocate other activities in overall business performance.

As the one of the dependent variables of the structural model, the attitude of an individual consists of feelings, thoughts and tendencies to act towards an aspect or move forward a direction. Attitudes represent an individual's tendency to feel, think or behave in a positive or negative direction (Vakola & Nikolaou, 2005). Attitude will affect the analytical thinking of the individual. Hence, employees who have a positive attitude towards using the system are more likely to use the business analytics (Mansell, 2015). In other words, according to the analysis results, a positive attitude toward using the business analytics tools leads to higher level of use of business analytics tools in the business processes.

Considering the control variables’ effect on the actual use of business analytics, firstly age factor was analyzed. In this study it was mostly worked with generation X and Y. Generation X are individualistic. They would like to manage their own time. Their determinant of work values are setting their own limits and do their tasks without supervision. They dislike rules. Work/life balance is very important for them. However, they are loyal to relationships, resilient, adaptable and open minded (Hendricks & Cope, 2012). On the other hand, generation Y thinks and acts a bit more differently. They have less loyalty to organization and can easily change jobs. They constantly seek career development. They are risk-takers who are familiar with non-routine and multitask. Generation Y gives more value work/life balance. Since they have grown up with technology, they are very comfortable with any technology, thus, diversity and change. They are technology dependent, indeed (Cennamo & Gardner, 2008; Nel, Werner, Botha, Du Plessies, Mey, Ngalo, Poisat, & Van Hoek, 2014). Considering these differences, it was thought that the age factor could have an impact on the use of business analytics. However, no significant effect was found. Employees of all age groups use the system in business processes, at similar levels. Secondly, gender factor was examined. The effect of gender on the actual use level was found insignificant as it explored in many studies (Gefen & Straub, 1997). Thirdly, the complexity level of business analytics software used was tested. Participants are using more than 10 different business analytics software while applying business analytics in business processes. Some are relatively much more complex than others. It was speculated that the complexity level of systems may affect the levels of use of the system. As expected, the impact of the system complexity on the level of use of business analytics in business processes was determined significant. Finally, experience level with business analytics was investigated. Having prior knowledge about customers, internal organizational issues and market is effective the individual's seeking of opportunities (Quan, 2012). Consequently, experienced employees with this awareness can be more open and willing to use analytics to obtain more potential implications for the organization (Mansell, 2015). Thus, as shown by the analysis results, it can be said that it is very likely that employees who previously used business analytics will use the similar systems more often.

Finally, the comparison test results show that the level of business analytics usage is influenced by both the degree of difficulty of the system and the capital structure of the organization that is being used. However, the differences in the main activity of an organization do not have any effect on any factor that has been examined. On the other hand, the evaluation of analytical performance is greatly influenced by the complexity of the business analytics system.

With these results, the research question has been successfully answered and this will hopefully lead to the successful achievement of the objectives of the research. In the light of these accomplishments, the implications of these objectives will be revealed in the next two sections.

5.2 Theoretical Contributions

Despite the fact that the technology acceptance model (TAM) has been studied in several studies for many different systems, specifically the factors that influence the use of emerging business analytics systems have never been researched. Although many studies are testing the basic model, this master thesis added three important construct to the TAM: *Analytical Decision Making Culture*, *Analysis Performance of the System*, and *Interface and Integration Quality of the System*. "System quality" construct are separated into two different dimensions. One group of items was measuring the analysis performance of the system, while the other group was composed of the items measuring the quality of the interface and the integration of the system with other operational systems in the organization. Thus, *System Quality* construct was divided into two constructs: *Analysis Performance of the System* and *Interface and Integration Quality of the System.* These two constructs have different impact on *Perceived Usefulness* and *Perceived Ease of Use*. While analytical performance of the business analytics system influences the perceived usefulness more, the quality of interface and integration with other operational systems has more impact on perceived ease of use.

Thus, while previous studies are only examining the fundamental relationships between the factors, in this research, antecedent relationships between the constructs which are constituted hypotheses that resulted from the literature review were tested on a wider frame, as well. As a result of examining a new and hot topic, with the new factors and new relationships, these contributions have completed the major gaps in the literature.

To conclude, the main theoretical contribution is to present the technology acceptance model in the business analytics context, by also examining the quality of system, and the role of analytical decision-making culture in the organization. This study will lead to gain a new perspective on data-driven decision making in business life due to the fact that there is not much research has not been done on the use of business analytics and thanks to the antecedent factors added to the technology adoption model.

5.3 Practical Contributions

This paper contributes to practice in three different ways. Firstly, statisticians will be able to integrate statistical analyzes into the system that are appropriate, useful and in line with the personal and organizational goals by providing a high analysis performance. Thus, integrated analyzes functions that are useful to employees' job tasks will affect the user's attitude in the positive direction and increase the use of business analytics systems. Secondly, system developers will be able to develop system features that make the system easy to use and useful. In particular, they will be able to give importance to the inspected most important factors that indicate the quality of the system, especially the interface and integration quality, from the user’s point of view. In this way, it can positively affect the user's usefulness and ease to use perception. Thirdly and most importantly, managers will be able to better manage business analytics investments that companies allocate a large portion of their budget. They will prefer to invest in the most useful system that supports the purpose of the company and its users. Easiness of use of a business analytics system is as important as its usefulness. Managers will begin to invest more in easy-to-use systems, even if the system is very useful for desired targets. In terms of the sectoral comparison, based on the capital structure, the level of business analytics usage level is different between the public and private sectors. Employees working in the private sector are using business analytics systems more intense. Thus, the managers in the private sector should benefit from this advantage and try to increase this level of utilization even further. On the other hand, managers in the public sector should raise awareness of the use of these kinds of systems. All organizations from both private and public sectors should inoculate positive attitude which is found as the most influential factor in use. This may be possible with proper trainings. Organizations need to increase awareness of analytics use and to support positive attitude towards to use of business analytics. Moreover, this study will improve the usage level of business analytics tools since managers will be able to objectively evaluate the factors affecting the use that are presented in this research. In addition, if especially top management depends on analytics and fact-based decision-making processes, the analytical decision-making culture will be developing much easier (Chan & Hernandez, 2011). For this reason, both top managers and employees should support the analytical capabilities and culture within the organization to ensure continued growth and success (Chan & Hernandez, 2011).

5.4 Limitations

The present research has several limitations that should be taken into account.

Firstly, this research has a limited sample size, this limitation mainly aroused associated with the way that the data were collected. Major portion of the questionnaires were distributed via web based. Although preliminary information was given just before the questionnaires were delivered and reminder e-mails were sent for unanswered questionnaires, many surveys were not filled in. Since this situation may cause nonresponse bias, some questionnaires were conducted via mail to organizations where many possible participants exist. That move minimized sampling bias in order to achieve representative sample of the population. Another reason to obtain a limited sample size is that many organizations are implementing business analytics initiatives newly. It means it is a very recent situation that analytical software starts to be used in organizations. Even in the large-size organizations, business analytics systems are not used by many people in the organization. Therefore, it would not be possible to reach more participants. Hence, this sample size (n=91) may be counted as sufficient.

Secondly, the questions with Likert-type scales are all basically measuring perception of participants. Even though this research focused on the individual level of attitude, intention, use, acceptance of the analytical systems, it is possible that individual responses may systematically vary according to personal or organizational characteristics. For instance, while speaking with some of the participants, they indicated that the trainings of data analysis software were not proper. According to them, it was neither easy to learn nor easy to use the system. Thus, "*Perceived Ease of Use*" construct is affected from their responses since the organization could not maintain a productive education process. This example and similar cases may limit the generalizability of the study results.

Thirdly, this study measured adoption and use behavior at a single point of time. Since the users' these behaviors are likely to evolve over longer time cycles and perception can change accordingly, longitudinal studies may provide more accurate results. For example, in a large-scale public organization, some of the users used Stata in business processes for a very long time, so they integrated the system more into their business and they could see the benefits of the system more clearly. However, some users in the same institution had just learned Stata and were using this system for less than a year. In this case, they have not yet completed the acclimatization phase and have not seen the full benefit of the system in their business processes. The adaptation process would be measured more properly if the new-users were measured again after a certain period of time.

Fourth, participants expressed their opinions for different statistical analysis programs. For instance, while R is a statistical programming language, SPSS is typical point-and-click software package. Moreover, R is known as not to be user friendly. The differences in the complexity level of the systems caused quite different answers to the same questions, especially in *Analysis Performance of the System, Interface and Integration Quality of the System* and *Perceived Ease of Use* factors. Besides, it is quite effective on the level of *Use of Business Analytics*. This situation was proven by the control variable of *System Complexity* analyzed and it was stated that it has significant effect on the ultimate use of business analytics.

Fifth, although no issues were detected in terms of discriminant validity cut-off levels, still a slightly high correlation appeared between *Attitude Toward Use* and the *Perceived Usefulness* constructs. One reason for such a powerful correlation between the two structures, which are conceptually very different from one another, may be that it is very difficult to measure these two sensitive psychological constructs with surveys.

Finally, participants working in the same company might have evaluated the organizational analytical decision-making culture differently. This has led to the perceptual measurement of analytical decision making culture rather than an objective measurement. In addition, some responses, especially the ones about *Analytical Decision-Making Culture* in the organization, might be given based on social desirability. However, since it is observed that such answers could not be avoided in particularly business investigations, this is not evaluated as a major bias.

In the light of all these limitations, for the future research, some suggestions are given in the next section.

5.5 Future Research

First of all, since *Business Analytics* is a relatively new topic that has a growing interest among researchers and practitioners, it will be exciting to follow how the field of Business Analytics will develop. Based on the findings of this research, it also will be interesting to see further research for their advancements and unique contributions.

Future improvements to the extended TAM could be done by applying it to different types of analytics software, separately. It would be more accurate to examine only one system. As a different viewpoint, it also could be applied to the similar types of users in terms of the similar level of experience with the system so that users who have overcome the learning phase and reached mature and effective use of the system would be measured. Moreover, further studies can analyze *Actual Use of Business Analytics* in the similar industrial settings. Each sector uses statistical analysis at different frequencies for different purposes in different functional areas. Examining TAM in this way would provide more precise results in terms of generalizability of the study.

In addition, different kinds of antecedents to the TAM could be analyzed more deeply. It is important to understand the components of *Perceived Usefulness* and *Perceived Ease of Use* of business analytics tools and follow current trends in specific user acceptance in analytics systems.

The present work did not investigate the effect of demographic variables as direct factors, but considered them as control variables. Therefore, future research could examine the effect of more demographic factors on business analytics systems adoption and use behavior. It is especially crucial to consider different personal (e.g. openness to innovation, risk-taking behavior, etc.) and organizational characteristics (e.g. top management commitment, organizational structure and size of the firm). This would enable to better understand the mechanism of successful integration of analytical systems into the business processes.

While delivering the questionnaire to the participants and informing them about the aim of the study, it was noticed that the employees who heard the content of the work had a lot to say in this regard. For this reason, in order to gain more insight, it can be added some qualitative questions to the study. Besides, to better evaluate the use and adoption behavior, study can be applied as longitudinal.

Finally, in order to increase the explanatory power of the model, it could be necessary to consider additional constructs to the TAM. Considering the nature of the business analytics usage, it would be appropriate to think of adding more factors that are system related and influenced by organizational culture such as accessibility, trialability, management support, and peer influence (Yousafzai et al., 2007).

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APPENDICES

A. SURVEY

Evaluation of Opinions Regarding the Use of Business Analytics in Business Processes

Dear participant,

In this study, it is aimed to discover the factors affecting the use of data analysis software in business processes. Your answers to questions on the questionnaire will be kept private and will be used purely for scientific purposes.

This questionnaire consists of two parts. The first part consists of questions prepared to obtain personal information and to measure system usage habits; the second part designed to determine your thoughts and opinions about the business analytics system you are using. Participation in this study takes 5-7 minutes on average.

Thank you in advance for your help and interest.

Assist. Prof. Dr. Melek AKIN ATEŞ
Thesis Student Nazlı BAYRAM

SECTION ONE

1. Age
   a. <30
   b. 30-39
   c. 40-49
   d. 50-59
   e. 59>

2. Gender
    a. Female
    b. Male
3. What is your highest level of degree?
    a. High school degree
    b. College/university degree
    c. Master degree
    d. Doctoral degree
4. In which sector do you work in terms of capital structure?
    a. Public sector
    b. Private sector
5. In which sector do you work in terms of activity area?
    a. Information technologies
    b. Finance and banking
    c. Regulating
    d. Healthcare
    e. Chemistry, foundry, and petroleum
    f. Fast-moving consumer goods
    g. Energy
    h. Automotive
    i. Defense
    j. Trade (sales and marketing)
    k. Service industry
    l. Other (Please specify:………………………………………)
6. How many full-time employees does your organization have?
    a. 0-50
    b. 51-250
    c. 251-500
    d. 501-1000
    e. More than 1000 employees

7. How often do you use information systems that enable to analyze data for business processes?
    a. Less than 1 year
    b. 1 to 3 years
    c. 4 to 6 years
    d. 7 to 9 years
    e. More than 9 years
8. In your business processes, which computer program do you use to analyze data? (If you are using more than one program, please indicate which program you use the most.)
    a. Business Intelligence System (BI)
    b. R
    c. SAP
    d. SAS
    e. SPSS
    f. Stata
    g. Other (Please specify:…………………………………………)

Please answer the following questions by considering the data analysis system that you indicated in the previous question.

9. How long have you been using this system?
    a. Less than 1 year
    b. 1-2 years
    c. 3-4 years
    d. 5-6 years
    e. More than 6 years
10. How often do you use this system?
    a. Several times a day
    b. About once a day
    c. 2 or 3 times a week
    d. About once a week
    e. 2 or 3 times a month

11. How much time do you spend in a day directly using this system?
    a. Less than 15 minutes
    b. 15-30 minutes
    c. 31-45 minutes
    d. 46-60 minutes
    e. More than 1 hour

SECTION TWO

In this section, several questions have been asked in order to learn about your views on data analysis software. Please take these questions in line with your own thoughts.

Please indicate to what extent you agree/disagree with the following items: (Scales are 1-5; where 1: strongly disagree, 2: disagree, 3: neutral (neither disagree or agree), 4: agree 5: strongly agree)

( ) 1. The speed of the system is sufficient.

( ) 2. The system content (the analysis functions presented, etc.) is quite extensive.

( ) 3. The interaction of the system with other operational systems used in my company is successful.

( ) 4.The system has a user-friendly interface.

( ) 5. The analysis results received from the system is reliable.

( ) 6. I do not suffer from any data loss in the system and the system safely stores the entire information.

( ) 7. The system provides the data in various formats according to the requests.

( ) 8. Using the system in my job enables me to accomplish tasks more quickly.

( ) 9. Using the system improves my job performance.

(   ) 10. The system makes it easier to do my job.

(   ) 11. The system provides support for important issues at work.

(   ) 12. Using the system increases my dominance at work.

(   ) 13. Overall, I find the system useful in my job.

(   ) 14. Learning to use the system was easy for me.

(   ) 15.Thanks to the system, I can easily do what I want to do about work.

(   ) 16. Using the system is clear and understandable.

(   ) 17. Using the system does not require a lot of mental effort.

(   ) 18. I do not need a manual when using the system.

(   ) 19. Overall, I find the system easy to use.

(   ) 20. Using the system is a pleasant experience for me.

(   ) 21. I feel using the system is a wise choice.

(   ) 22. I think that by using the system, we would achieve certain strategic advantages.

(   ) 23. Overall, I have a favorable attitude towards using the system.

(   ) 24. I intend to use the system regularly at work.

(   ) 25. When I need to do an analysis, I prefer using the system.

(   ) 26. It is likely that I will use the system in the future.

(   ) 27. In my organization, I believe that decisions are given primarily based on rational analysis.

(   ) 28. In my organization, the data-based decision-making process is well established and known to its stakeholders.

(   ) 29. It is my organization's policy to incorporate available information within any decision-making process.

(   ) 30. Small or big in any decision making process, we take into account the available information.

(   ) 31. In my organization, supervisor(s) encourage(s) me to consider every situation from all angles.

( ) 32. In my organization, supervisor(s) encourage(s) me to work detailed and methodical.

( ) 33. I use the system regularly.

Thank you for participating in our survey. For more information about the study, you can contact with Assist. Prof. Dr. Melek Akın Ateş (e-mail: mates@metu.edu.tr) or thesis student Nazlı Bayram (e-mail: nazli.bayram1@gmail.com). Please note that if you wish to receive a brief summary of this survey and thesis results, please indicate your email address below.

E-mail:…..………………………………………………………………………

B. ETHICS APPROVAL DOCUMENT

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05 NİSAN 2018

Konu: Değerlendirme Sonucu

Gönderen: ODTÜ İnsan Araştırmaları Etik Kurulu (İAEK)

İlgi: İnsan Araştırmaları Etik Kurulu Başvurusu

Sayın Melek Akın ATEŞ

Danışmanlığını yaptığınız Nazlı BAYRAM'ın **"Örgütlerde İş Analitiği Sistemlerini Benimseme ve Kullanma Sürecini Etkileyen Faktörler: İş Analitiği ile Veriden Bilgiye"** başlıklı araştırması İnsan Araştırmaları Etik Kurulu tarafından uygun görülerek gerekli onay **2018-SOS-064** protokol numarası ile **06.04.2018 - 30.09.2018** tarihleri arasında geçerli olmak üzere verilmiştir.

Bilgilerinize saygılarımla sunarım.

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Üye

C. PRELIMINARY MEASUREMENT MODEL ANALYSIS

Table 13

Correlations between the Latent Variables and Square Roots of the Average Variance Extracted

	Actual Use of Business Analytics	**Analytical Decision-Making Culture**	**Attitude Toward Use**	**Perceived Ease of Use**	**Perceived Usefulness**	**Analysis Performance**	**Interface and Integration Quality**
Actual Use of Business Analytics	0.886						
Analytical Decision-Making Culture	0.321	0.882					
Attitude Toward Use	0.529	0.554	**0.886**				
Perceived Ease of Use	0.506	0.488	0.628	0.800			
Perceived Usefulness	0.630	0.584	**0.852**	0.641	0.862		
Analysis Performance	0.442	0.324	0.692	0.347	0.660	0.749	
Interface and Integration Quality	0.299	0.488	0.556	0.601	0.601	0.443	0.885

Note. The square root of average variance extracted (AVE) is presented on the diagonal of the correlation matrix and inter-construct correlations are presented off the diagonal.

D. FIGURES

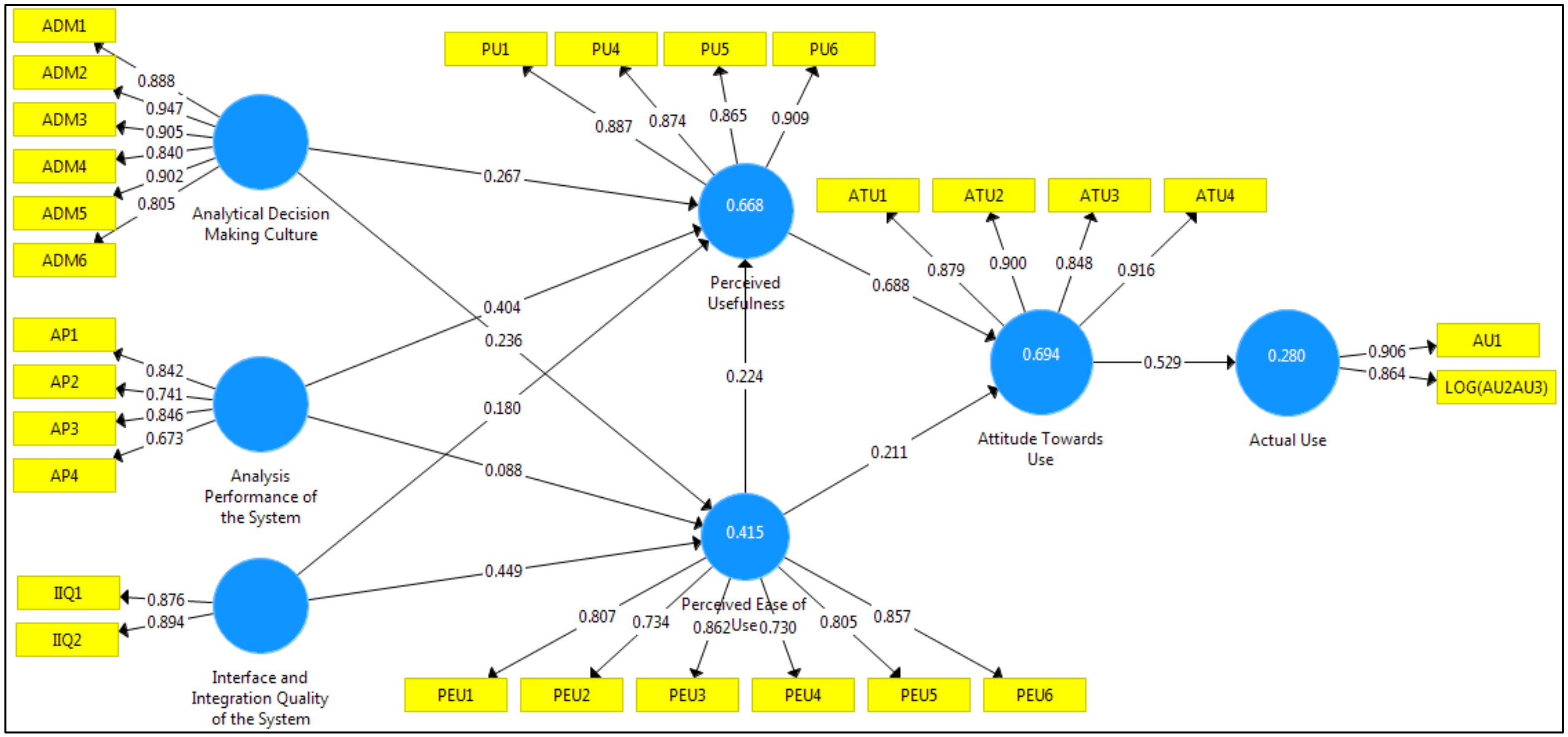

Figure 10. *Path Coefficients*

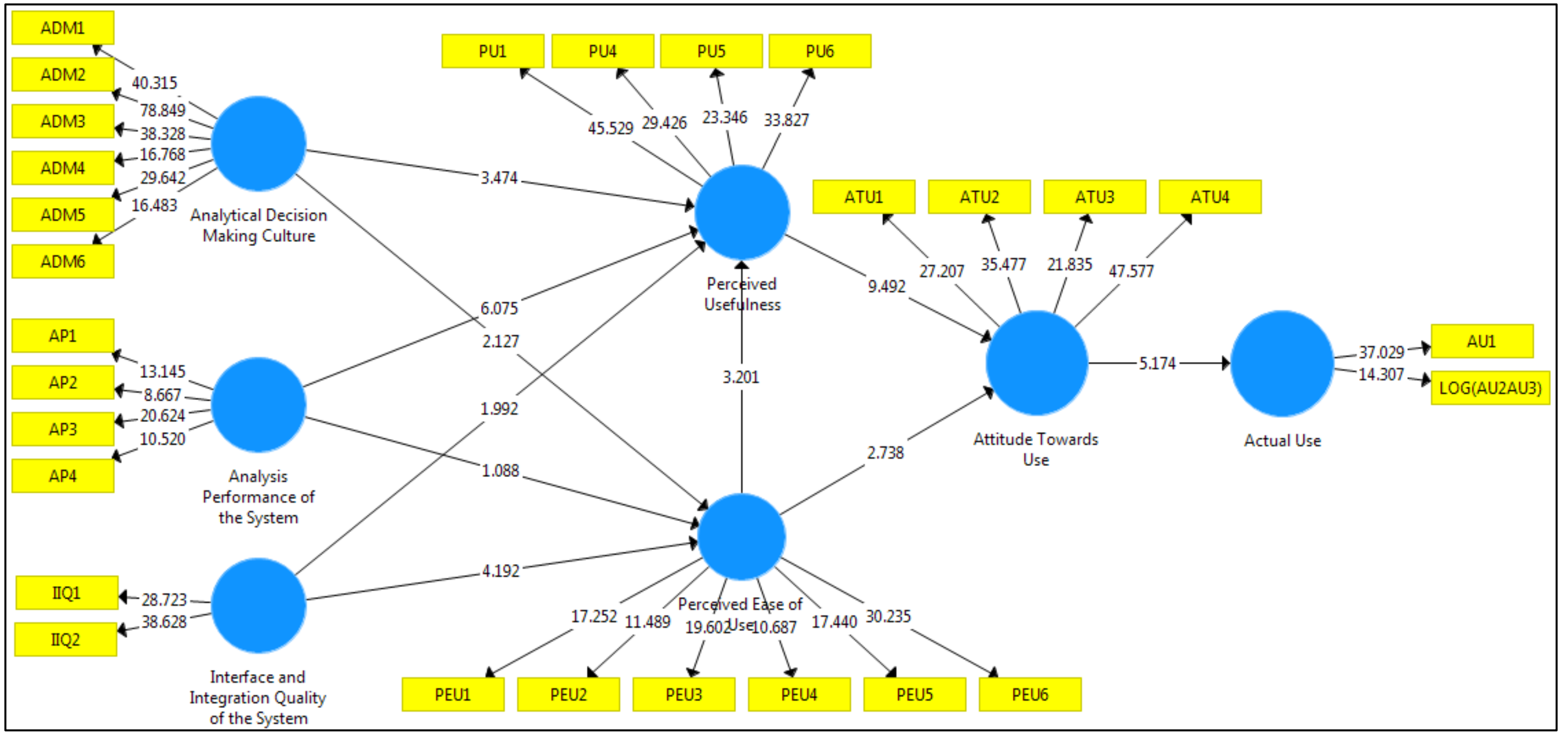

Figure 11. *Significance Statistics: t-stats*

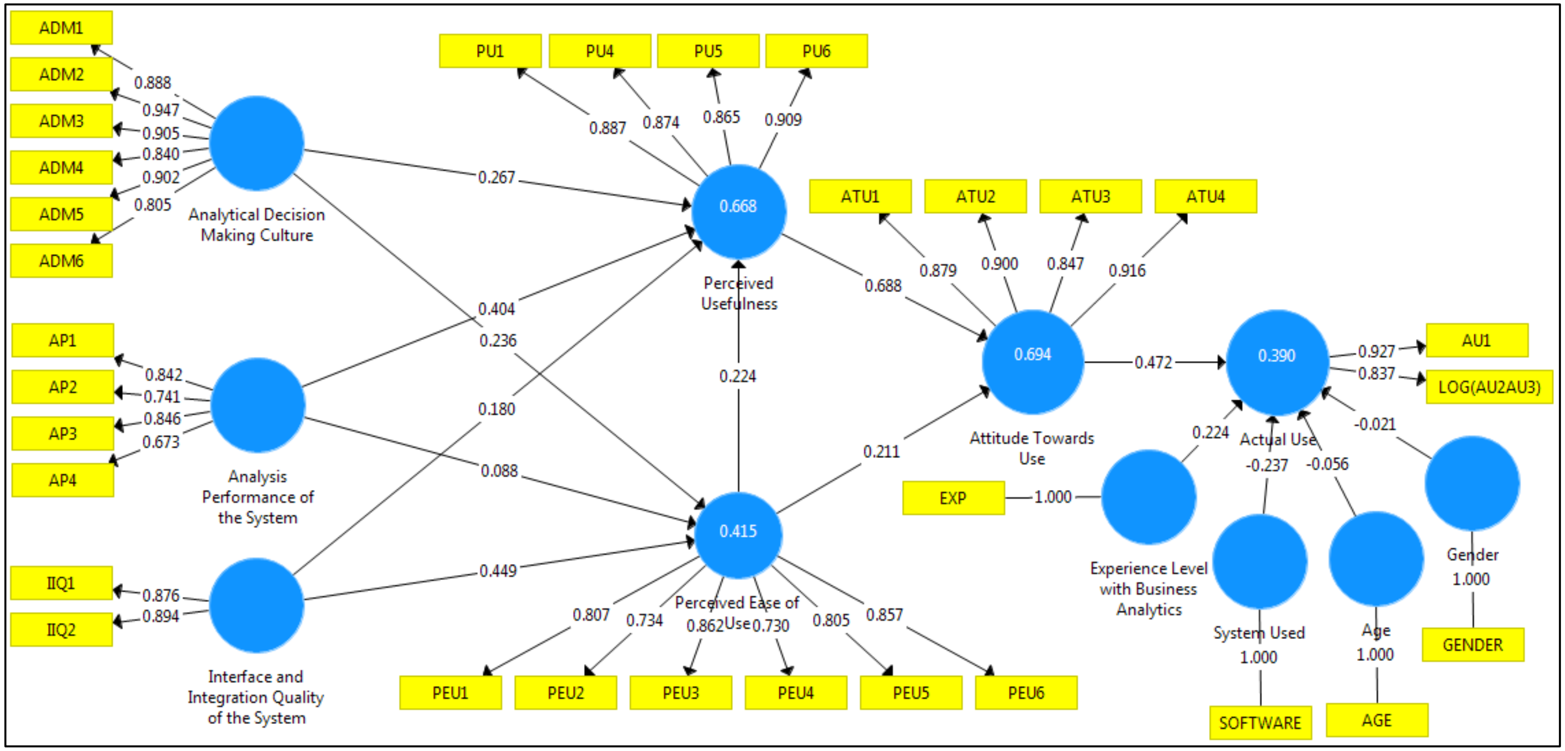

Figure 12. *Path Coefficients with Control Variable*

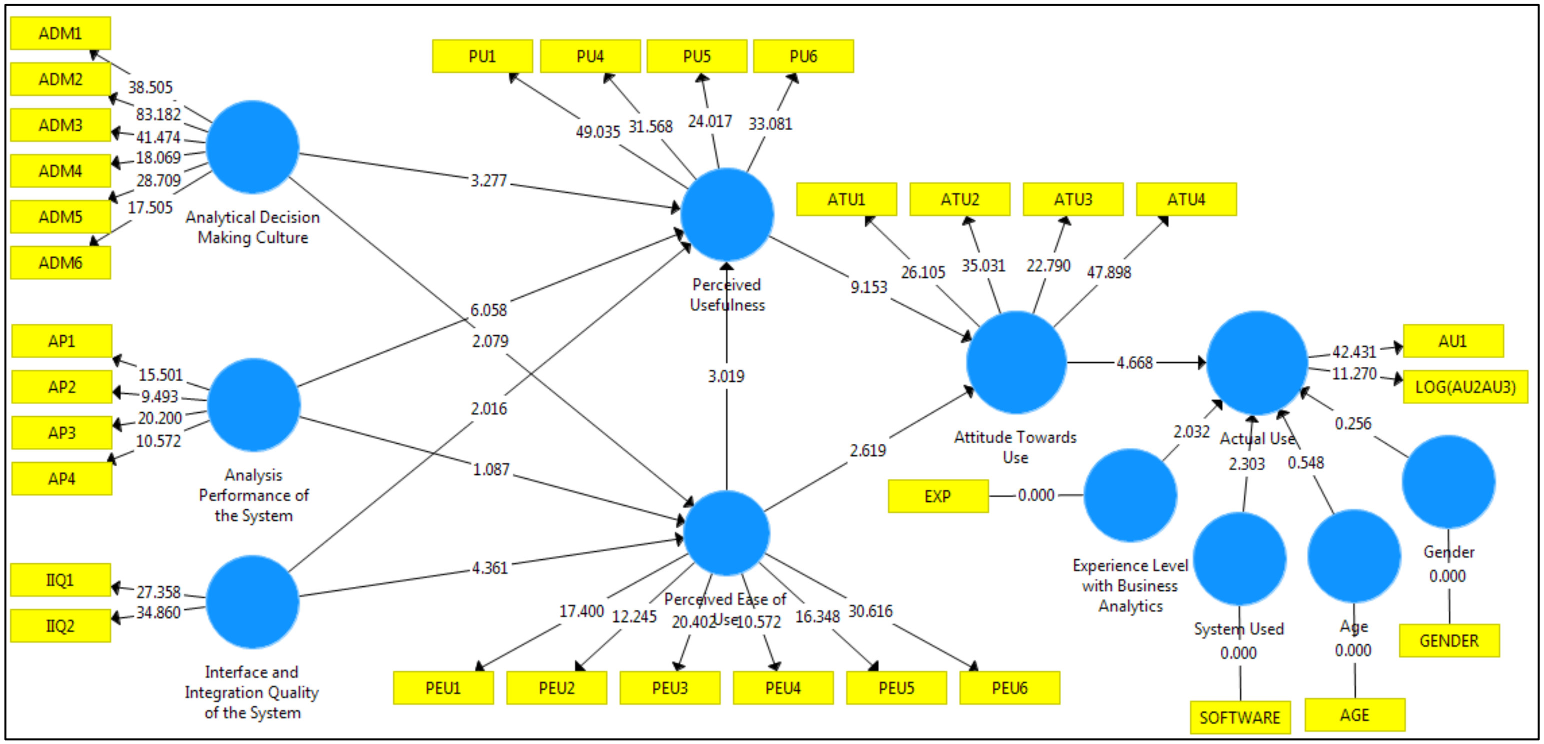

Figure 13. *Significance Statistics: t-stats with Control Variables*

E. TURKISH SUMMARY / TÜRKÇE ÖZET

1. Giriş

Veri her zaman çok değerli olmuştur. Ancak, verileri ölçülebilir bir varlık olarak ele almak dünyanın bakış açısını değiştirmiştir. İstatistik bilimi, verileri çeşitli ölçme fonksiyonları ile bilgiye dönüştüren değerli bir bilim dalı olmaktan çok daha fazlasıdır; içgörü sağlar, ama en önemlisi değer katar.

Öyle bir çağda yaşıyoruz ki, sadece veriyi akıllıca kullananların başarıya ulaşması mümkündür. Bu durum, tam olarak analitik ve iş dünyasının kesişme sebebidir. Kullanıcılar, özellikle de şirketler ellerindeki verileri doğru bir şekilde analiz edebilirlerse, yararlı bilgiyi bu yolla çıkarabilirler. Bu bilgiler şirketlerin refahı ve karlılığı için kullanıldığı takdirde, bilgeliğe dönüşmektedir. Bu bilgelik organizasyonlara büyük bir rekabet avantajı sağladığı için iş hayatında iş analitiği vazgeçilmez olmuştur (Stubbs, 2011).

İş analitiği, basit veya gelişmiş analiz yöntemlerinden daha fazlasıdır. İş analitiği temel olarak bunların bütünüdür, ek olarak kullanılan bu analiz fonksiyonlarını iş eylemlerine dönüştürür. İş analitiği "temel işletme hedeflerine bağlı ileriye dönük iş sorularına cevap vermek ve hareket etmek için gerekli olan, kurum içinde ve dışındaki farklı veri kaynaklarının analitik entegrasyonu" (Isson ve Harriott, 2013, s.3) veya kısaca "iş durumları bağlamında gerçekleşen problemleri veriye dayalı olarak tanıma ve çözme eylemleri bütünü" (Holsapple, Lee-Post ve Pakath, 2014, s.134) olarak tanımlanır.

İş analitiği, verilerin analiz edilmesine ve analiz sonuçlarının iş eylemlerine aktarılmasına olanak tanıyan işlemler ve iş süreçleri arasında iki yönlü bir döngü oluşturur. Bu döngüde ortaya çıkan bilgi, işletme çalışanları tarafından günlük faaliyetlerinde kullanılmaktadır (Kohavi, Rothleder ve Simoudis, 2002). Verilerin bilgiye dönüştürülmesi tamamlandıktan sonra, iş analitiği organizasyon için stratejik değer yaratarak, rekabet avantajı yaratmakta ve kurumsal stratejiyi desteklemektedir (Stubbs, 2011).

İş analitiği çeşitli yöntemlerle uygulanabilir durumdadır. Kalem ve kağıt ile yapılmaya başlanmış ama günümüzde açıklayıcı ve tahmin modelleri sunan SAS modülleri gibi son derece gelişmiş ve karmaşık sistemlerle uygulanmaya devam etmektedir (Ahmed ve Ji, 2013).

"İş Analitiği" kavramı, Frederick Winslow Taylor'ın 1911'de "Principles of Scientific Management" adlı kitabında *Bilimsel Yönetim* bağlamını sunduğunda ortaya çıktı. Fakat bu konu, bilgi sistemleri konusunda çalışan araştırmacıların 70'li yıllarda "Karar Destek Sistemi" çalışmalarıyla zirveye ulaşmaya başlamıştır. Kuruluşlar, hem idari operasyonlar sırasında karar verme süreçlerini desteklemek hem de kritik bilgilerin zamanında ve güvenilir bir şekilde gerekli birimlere ulaşmasını sağlamak için iş analitiği kullanır. Başka bir deyişle, iş analitiği, kritik bilgiye daha hızlı ve daha güvenilir bir şekilde ulaşarak bir organizasyondaki veriye dayalı karar destek mekanizmasını desteklemeyi sağlayan yararlı bir araçtır. Veri odaklı iş ortamına sahip işletmeler, çalışanlarının iş analitiği yardımıyla doğru kararlar alabilmesi ile çok daha başarılı olabilir. İş analitiği ile iş süreçlerini yönetmek, sistematik kararlar verilmesini sağlar, böylece iş durumlarında daha az hata gözlenir (Provost ve Fawcett, 2013).

İş analitiği sayesinde elde edilen gelir, International Data Corporation (IDC) 2016 yılında 130,1 milyar dolar olarak hesaplanmıştır ve 2020 yılında 203 milyar dolardan fazla bir değere ulaşacağını tahmin etmektedir (Press, 2017).

Bu denli fayda sağlayan iş analitiği için yıllık iş analitiği yatırımlarının sadece kamu, finans, enerji ve haberleşme sektörlerinde 2020 yılına kadar %22'den %54'e çıkacağını tahmin edilmektedir (Villanova Üniversitesi İşletme Makaleleri, n.d.). Sonuç olarak, organizasyonların iş analitiğine verdiği önem her geçen gün büyümekte ve daha da büyümesi beklenmektedir.

Organizasyonlar birçok farklı nedenden dolayı bilgi sistemlerine yatırım yapmaktadır. İş analizinin söz konusu tüm faydaları hesaba katılırsa, bu sistemlerin kuruluşlarda kullanılmaması çok mantıksız görünmektedir. Bununla birlikte, çalışmalar, iş analitiğinin, kuruluşlar arasında ve hatta aynı kuruluştaki çalışanlar arasında bile aynı ölçüde kullanılmadığını göstermektedir (DecisionPath Consulting, 2010). Araştırmacılar, bilişim sistemlerinin iş dünyasında kullanımını artırabilecek faktörlere odaklanmışlardır. Bu konu ile ilgili olarak, doktora çalışmasında Davis (1986) teknoloji kabul modelini önermiştir. O zamandan beri teknoloji kabul modeli, e-posta kullanımı (Davis, 1986), çevrimiçi alışveriş (Devraj, Fan ve Kohli, 2002) ve interaktif TV (Choi ve diğ., 2003) gibi çeşitli bağlamlarda birçok araştırmada test edilmiş ve genişletmiştir. Teknoloji kabul modeli, çeşitli teknolojilerin benimsenmesi ve kullanımını incelemek için pek çok kez araştırma konusu olsa da, iş analitiği sistemleri üzerinde daha önce uygulanmamıştır. Literatürdeki bu boşluğu doldurmak için, bu yüksek lisans tezinde teknoloji kabul modeli, iş süreçlerinde iş analitiği sistemlerinin kullanımını etkileyen faktörleri ortaya koymak amacıyla incelenmiştir. Çoğu çalışma iş analitiğini bilgisayar bilimi perspektifinden incelenmiştir. Ancak bu çalışma konuyu işletme perspektifinden ele almıştır. Bu araştırmada, genişletilmiş teknoloji kabul modeli altında işletmelerde iş analitiği kullanımı araştırılmıştır. Sistemin algılanan faydası ve algılanan kullanım kolaylığı, en etkili ve temel faktörler olarak değerlendirilerek, kullanıma yönelik tutumu olumlu yönde etkilediği öngörülmüştür. Teknoloji kabul modelinin öncülleri olarak, sistemin analiz performansı, sistemin arayüz ve organizasyondaki diğer operasyonel sistemlerle entegrasyon kalitesi teknolojik faktörler olarak araştırılmış, analitik karar verme kültürü ise örgütsel bir faktör olarak incelenmiştir. Son olarak, yaş, cinsiyet, kullanılan yazılımın zorluk derecesi ve tecrübe, iş analitiğinin kullanımını etkileyen kontrol değişkenleri olarak incelenmiştir.

Bir sonraki bölümlerinde, sırasıyla araştırmanın amaçları, araştırma sorusu, araştırma kapsamında incelenen faktörler, araştırma yöntemi ve son olarak bulgular açıklanmaktadır.

2. Araştırma Amaçları

Makalenin bu bölümünde, çalışmanın amaçları teorik ve pratiğe yönelik hedefler olarak iki boyutta belirtilmiştir.

2.1. Teorik Hedefler

İş analitiğinin değerinin arttığı ve kanıta dayalı yönetimin gün geçtikçe yaygınlaştığı bir gerçektir. Şirketler, veriye dayalı kararlar vermek için farklı analitik araçlara yatırım yapmaya ve kullanmaya başladı. Fakat organizasyonlarda veri temelli karar vermeyi sağlayan ve destekleyen bilgi sistemlerinin kullanımını etkileyen faktörler daha önce kapsamlı bir şekilde incelenmemiştir. Literatürün çoğu, iş analitiğinin iş süreçlerinde kullanılmasını sağlayan sistemleri incelemekten ziyade, operasyonel yönetimi kolaylaştıran ve kuruluşlar için basit raporlama sağlayan sistemlerin kullanımını etkileyen etkenleri araştırmaktadır. Bu nedenle, bu çalışmada, iş analitiği sistemlerinin kullanımı ve benimsenmesini etkileyen faktörler, bu açıdan en temel teorilerden biri olan teknoloji kabul modeline dayanılarak çalışılmıştır. Teknoloji kabul modeli ışığında *Algılanan Fayda* ve *Algılanan Kullanım Kolaylığı* iki ana faktör olarak çalışılmıştır. Ayrıca, tutumun kullanım üzerindeki doğrudan etkisi analiz edilmiştir.

Teknoloji kabul modeli, temel olarak algı ve tutum gibi bireysel faktörleri ele almaktadır. Ancak, iş analitiği araçlarının kullanımı analiz edilirken, kişisel faktörlerin yanı sıra, örgütsel ve teknolojik faktörler de önemli bir rol oynamaktadır. Bu gerçek dikkate alındığında, bu çalışmanın iki büyük katkısı vardır. Birincisi, teknoloji kabul modeline öncülük eden organizasyonla ilişkili bir faktör olarak *Organizasyonda Analitik Karar Verme Kültürü* eklenmiştir. İkinci olarak, teknoloji ile ilgili faktörler; *Sistemin Analiz Performansı, Sistemin Arayüz ve Entegrasyon Kalitesi* teknoloji kabul modelinin ikinci ve üçüncü öncül faktörleri olarak modele dâhil edilmiştir. Bu faktörlerin tümü, organizasyonlarda iş analitiği araçlarının adaptasyonunu ve kullanımını etkileyen önemli değişkenler olarak düşünülmüştür.

Bu yüksek lisans tezinin temel teorik amacı, iş analitiği bağlamında teknoloji kabul modelini test etmek ve bu modele eklenen örgütsel ve teknolojik düzeyde öncülleri de inceleyerek teoriye katkıda bulunmaktır. İş analitiğinin örgütsel karar verme mekanizması üzerindeki etkisi yadsınamaz olsa da, kanıta dayalı karar alma sürecine tam entegrasyon tüm kuruluşlar için henüz tamamlanmamıştır. Dolayısıyla, teoriye katkıda bulunmak için iş analitiği araçlarını benimseme ve devamlı kullanım sürecini etkileyen en önemli faktörleri belirlemek oldukça önemlidir. Modeldeki yapıların çoğu bilindiğinden bu çalışma genel olarak teori-test araştırması olarak kabul edilmesine rağmen, yeni öncül faktörlerin modele katılması nedeniyle, bu çalışma aynı zamanda bir teori geliştirme araştırmasıdır.

2.2. Pratiğe Yönelik Hedefler

İş analitiği sistemleri için özel olarak geliştirilen teknoloji kabul modelinin benimsenmesi birden fazla taraf için yararlı olacaktır. İlk olarak, istatistiksel analiz araçlarını tasarlayan istatistikçiler, şirketlere fayda sağlayacak en kullanışlı iş analitiği araçlarını sisteme entegre edebilecektir. Ayrıca, uygunluğuna göre hangi analiz fonksiyonlarının hangi araçlara entegre edilmesi gerektiğine de karar verebileceklerdir. İkincisi, sistem tasarımcıları, kullanıcıların analizleri daha kolay bir şekilde uygulamalarını sağlayacak kullanıcı dostu bir tasarım oluşturabilecektir. Üçüncü olarak, yazılım geliştiricileri sistemi istatistikçilerden ve tasarımcılardan aldıkları bilgiler doğrultusunda geliştirebilecek, kaynaklarını öncelikli alanlarda kullanabilecek, maliyeti doğru bir şekilde yönetebilecek ve uygulama sırasında ortaya çıkabilecek olası sorunları erken teşhis edebileceklerdir. Sonuncu ve en önemli katkı ise, veriye dayalı karar verme kültürü ile ilgili olarak, bu tez yöneticilere iş analitiği sistemlerinin kullanımını etkileyen faktörleri genel olarak anlamada yardımcı olabilir. İş analitiği araçlarını herhangi bir sisteme entegre ederken ve kullanıcılar arasında iyi bir iletişim kurmak başarılı bir proje yönetimini sağlar. Bir organizasyonda başarılı bir şekilde ele alınan faktörler sayesinde, yöneticiler iş uygulamaları ve müşteri davranışları hakkında daha fazla bilgi edinebilecektir. İş analizi, yapılandırılmamış büyük veri kümelerini daha iyi iş kararlarına dönüştürür. Böylelikle karar verici, şirketin kaynaklarını, potansiyel yatırımlarını ve müşteri ilişkilerini iyi yönetebilir. Bu durum da işletme verimliliğini artıracaktır (Elbashir, Collier, ve Davern, 2008). Buna ek olarak, yöneticiler, müşteri davranışları ve pazar eğilimlerini sürekli takip ederek öngörülebilirliği geliştirebilecektir. Şirketler, iş modellerinde potansiyel sorunların belirtilerini tespit etmek için operasyonlarını daha iyi planlayabilir ve iş faaliyetlerinin belirsizliği ile baş edebilirler. Ayrıca, şirketler doğru kararlarla hızlı bir şekilde hareket edebileceklerdir. Zamanında alınan kararlar, yoğun ve küresel rekabette büyük rekabet avantajı sağlamaktadır (Min, 2016).

Genel olarak, iş analitiği araçları müşteri ilişkileri yönetimi (CRM), tedarik zinciri yönetimi (SCM), kurumsal kaynak planlaması (ERP) ve iş zekası (BI) sistemleri gibi birçok sisteme entegre edilebilir. Ayrıca, R, Python, SPSS, SAS ve Stata gibi sadece istatistiksel analizlere izin veren programlama dilleri ve paket programları yoluyla da uygulanmaktadır. Bu çalışma, uygulayıcılar ve kullanıcılar tarafından, sistem kullanımında hangi faktörlerin önemli olduğu ve buna bağlı olarak, sistemin devamlı kullanımını destekleyecek bir sistem tasarımı, sistem geliştirmesi ve etkili proje yönetimi aşamalarında hangi eylemlerin gerçekleştirilmesi gerektiği konusunda bir ön değerlendirme olarak kullanılabilir.

3. Araştırma Sorusu

Kararlar, sezgi ya da duygular temelinde alındığında çok riskli sonuçlar doğurabilir (Maisel ve Cokins, 2015). Dolayısıyla, insan faktöründen bağımsız olan rasyonel analizin, örgütlerin yönetimini ve alınan kararları olumlu yönde etkilediği söylenebilir. Bu araştırmanın temel amacı işletmelerde iş analitiğinin kullanımını etkileyen faktörleri araştırmaktır. Bu nedenle, iş analitiği yatırımlarına yatırım yapan organizasyonlardaki çalışanlar tarafından iş analitiği yazılımlarının kullanımını etkileyen faktörleri incelemek kritik bir noktadır. Bu hedefin ışığında, ana araştırma sorusu aşağıda belirtilmiştir:

"Çalışanın iş analitiği uygulamalarının kullanımını etkileyen faktörler nelerdir?"

Bu konuyu incelemek için literatür, temel modellerden biri olan teknoloji kabul modelini işaret etmektedir. Ancak, bu modelin her bir çalışmada farklı sistemler için incelenmesinden dolayı revize edilmiş teknoloji kabul modelleri arasındaki karmaşıklık ve çeşitlilik araştırmacılar tarafından bilinmektedir. Bu çalışmada, teknoloji kabul modeli iş analitiği yazılımı için analiz edilmiştir. Bu bağlamda, sadece temel modeldeki ana yapılar geçerli olmayabilir, ek yapılar ile birlikte sistemin gerçek kullanımı daha iyi açıklanabilir. Geniş bir literatür taramasıyla, temel faktörler incelenmiş ve hipotezler formüle edilmiştir.

4. İş Süreçlerinde İş Analitiğinin Kullanımını Etkileyen Faktörler

Araştırmanın bu bölümünde, iş süreçlerinde iş analitiği sistemlerinin kullanımını etkileyen faktörler açıklanmıştır.

4.1. Kullanıma Yönelik Tutum

Tutum, "Bireyin hedef davranışı yerine getirme konusundaki olumlu ya da olumsuz duyguları" olarak tanımlanmıştır (Fishbein ve Ajzen, 1975, s.216). Sistemin kullanımına yönelik tutum ise, bireyin ilgili sistemi kullanma konusundaki değerlendirme etkisinin derecesini ifade eder (Fishbein ve Ajzen, 1975). Davis'in (1989) çalışmasının yayınlanmasından sonra tutumun, bir sistemin gerçek kullanımı üzerinde önemli bir etkisi olduğu anlaşılmış ve bu ilişkinin doğruluğunu kanıtlamaya yönelik düzinelerce çalışma devam etmiştir.

Teknoloji kabul modeline göre, potansiyel bir kullanıcının belirli bir sistemi kullanma konusundaki genel tutumunun, onu kullanıp kullanmadığının ana belirleyicisi olduğu varsayılmaktadır. Öte yandan, kullanım konusundaki tutumun iki temel faktörden etkilendiğine inanılmaktadır: *Algılanan Fayda* ve *Algılanan Kullanım Kolaylığı* (Davis, 1985). Davis (1993) tutum ve fiili kullanım arasındaki anlamlı ilişkiyi açıklamıştır. Igbaria'nın çalışmaları (1993; 1994), tutumun davranışsal niyet üzerinde pozitif bir etkiye sahip olduğunu doğrulamaktadır.

4.2. Algılanan Fayda ve Algılanan Kullanım Kolaylığı

Sistemin kullanımını etkileyebilecek birçok neden arasında, Davis (1989) iki ana belirleyiciyi tanımlamıştır. Bir sistemin gerçek kullanımını etkileyen en önemli faktörlerden biri algılanan faydadır. Davis (1989), algılanan faydayı "belirli bir sistemi kullanmanın bir bireyin açısından kendi iş performansını geliştireceğine inanma derecesi" olarak tanımlamıştır (s. 320). Çalışanlar, işlerini yapmalarına yardımcı olacağına inandıkları takdirde bir sistemi kullanmaya isteklidir. Algılanan faydası yüksek bir sistem, kullanıcılar için yüksek kullanım performansı sağlar (Davis, 1989). Ayrıca, algılanan fayda ve bir sisteme karşı tutum arasında da anlamlı bir ilişki vardır.

Bir organizasyonda, iş analitiği birçok farklı amaç için kullanılır. Bu amaçlar arasında en önemlisi, organizasyona değer katacak kararlar almaktır. Kuruluştaki sistem kullanıcıları düzenli olarak kurumun stratejik kararları için bu araçları kullanırlarsa ve başarılı geri dönüşler alırlarsa, tutumları olumlu yönde gelişecektir. Dolayısıyla, kullanıcı iş analitiğinin kurumun refahı için yararlı olduğuna inanıyorsa, tutumları olumlu yönde gelişecektir.

İkincisi, bir sistem çok faydalı olsa bile, potansiyel kullanıcılar, kullanımının çok zor olduğuna ve sistemi kullanma çabalarının, sistemin sağladığı faydalarından daha fazla olduğuna inanabilirler (Davis, 1989). Dolayısıyla, faydasına ek olarak, kullanım ve kullanıma yönelik tutum, algılanan kullanım kolaylığı tarafından etkilenir. Algılanan kullanım kolaylığı, "bir bireyin belirli bir sistemi kullanmanın fiziksel ve zihinsel çaba gerektirmeyeceğine inanma derecesi" olarak tanımlanmaktadır. (Davis, 1989, s. 320). Çaba, bireyin çeşitli faaliyetler için yapabileceği sınırlı kaynaktır (Radner ve Rothschild, 1975). Kullanıcının, kullanımı daha kolay olan bir uygulamayı kabul etmesi daha olasıdır (Davis, 1989).

4.3. Sistemin Analiz Performansı ve Arayüz ve Entegrasyon Kalitesi

Sistemin analiz performansı bir analizin tamamlanma hızını, kullanıcıya sunulan analiz fonksiyonlarının çeşitliliğini ve analiz sonuçlarının güvenilirliğini yansıtır. Sistemin arayüz ve entegrasyon kalitesi, kullanıcı dostu bir ara yüze sahip olmasının ve sistemin organizasyondaki diğer işletim sistemlerine entegre olmasının ölçüsünü gösterir. Bu iki teknolojik faktörün algılara olan etkileri farklıdır. Fakat her iki faktörün de algılanan faydayı ve algılanan kullanım kolaylığını etkilemesi beklenir.

4.4. Analitik Karar Verme Kültürü

Araştırmacılar, iyi verilmiş bir kararın, doğru zamanda doğru verilere sahip olma ve doğru bir şekilde analiz etmeyi temel aldığını savunmaktadırlar (Remus ve Kottemann, 1986). Sezgiye dayalı karar verme ile, veri toplama ve işleme aşamalarında, insan doğası nedeniyle bazı yanılgıların ortaya çıkması olasıdır. Organizasyonlarda gerekli veriler bazen yöneticinin görsel ve işitsel duyularıyla toplanır. Bu aşamada, bir karar vericiye veri sunma ile ilgili yanılgı ortaya çıkabilir. Bu hataların devam etmesinin nedeni, insan beyninin nörofizyolojik sınırlamalarıdır (Remus ve Kottemann, 1986). Bilgi işlem aşamasında, beyindeki her veri noktası arasındaki bağlantıların kurulması bazı yanılgılara yol açar. Bu hatalar, beynin organizasyonunun işlevi nedeniyle devam eder. Diğer taraftan, veriye dayalı veya analitik karar verme ile, kararlar yalnızca sezgiden ziyade, verilerin analizine dayanarak yapılır (Provost ve Fawcett, 2013). Bir organizasyonda analitik karar verme kültürü oluşturmak önemli bir adımdır çünkü birçok potansiyel faydası vardır. NewVantage Partners'ın üst düzey şirket yöneticilerinin yaptığı ankete göre, katılımcıların% 85'inden fazlası, şirket içinde veri odaklı bir kültür oluşturmak için bazı programlar başlattıklarını söyledi. Ancak, şu ana kadar bu programların sadece

%37'si başarılı oldu. NVP raporuna göre, sorun teknoloji ile ilgili değildi. Başarısızlık yönetim anlayışı ve genel örgütsel direnç ile ilişkiliydi (Press, 2017). Phillips ve diğ.'nin (1994) çalışmasının en önemli keşiflerinden biri organizasyonel kültürün bir teknolojinin benimsenmesine etkisidir. Analitik kültürel yatkınlığın, algılanan kolaylık ile fayda üzerinde anlamlı ve pozitif bir etkisi olduğu bulunmuştur (Phillips ve diğ., 1994). Bir işletmede analitik karar verme kültürü mevcutsa veya kurulabiliyorsa, iş analitiğine ilişkin genel fayda ve kolay kullanım algısı olumlu etkilenecektir.

5. Yöntem

Çalışmanın bu bölümünde örneklem yaklaşımı açıklanmıştır. Öncelikle ülke ve endüstri seçimleri kısaca açıklanmakta, ardından şirket ve katılımcı seçimleri netleştirilmektedir.

Bu çalışmada, araştırma stratejisi olarak anket araştırması uygulanmıştır. Bu araştırma temel olarak bireylerin belirli sistemler hakkındaki algılarına dayandığından, anket yaklaşımı, araştırma hedeflerine ulaşmak için en uygun yoldur. Ayrıca, teknoloji kabul modeline dayanan çalışmaların neredeyse tamamı anket yöntemi kullanılarak araştırılmıştır. Bu nedenle, veri toplama yöntemi olarak anket uygulanması seçilmiştir.

Araştırma sorumuz, iş analitiği sistemlerinin bireysel düzeyde kullanımına odaklandığından, bu araştırma için analiz birimi, kuruluşlarında iş süreçlerinde iş analitiğini kullanan çalışanlardır. Bu çalışma için 15 şirketten oluşan liste oluşturulmuş ve bu firmalardan temsilcilerin katılması istenmiştir. Anketler, iş analitiği konusunda ve organizasyonunda karar verme mekanizması için mevcut bilgilerin kalitesi hakkında bilgi sahibi olduğu tahmin edilen çalışanlara yöneltilmiştir.

İş analizi, hem akademisyenler hem de sistemi birebir kullananlar için oldukça yeni bir konudur. İstatistik analizine dayanan karar verme kültürü, tüm dünyada yeni yeni oluşmaktadır. Teknoloji kabul modeli sistem adaptasyonunun doğru bir şekilde incelenmesi için genellikle bir sistemin uygulanmasının erken veya orta evresinde kullanılır. İş analitiği sistemlerine yatırım yapma ve iş süreçlerinde kullanma konularında oldukça yeni olduğu için, bu çalışmayı gelişmekte olan ülkeler üzerinde uygulamak daha doğru olacaktır. Bu amaçla gelişmekte olan ülkelerden biri olarak, Türkiye veri toplama ve analiz için seçilmiştir. İş analitiğinin farklı iş süreçlerindeki rolünü araştırabilmek için, hem kamu hem de özel sektörden farklı endüstrilerde çalışan kuruluşlar örneklemde yer almıştır. Bu işletmeler arasından, kullandıkları sistemin karmaşıklığı veya sistem kullanım düzeylerine bakılmaksızın organizasyonlar seçilmiştir. Veriler, Türkiye'de faaliyet gösteren 15 küçük, orta ve büyük ölçekli işletmeden anket yoluyla toplanmıştır. Bu kuruluşlar, bilişim teknolojileri, finans ve bankacılık, düzenleme, sağlık, kimya, döküm, petrol, hızlı tüketim malları, enerji, otomotiv, savunma, ticaret (satış ve pazarlama), hizmet sektörü (insan kaynakları ve marka ve patent sektörü) gibi geniş bir yelpazede faaliyet göstermektedir. Bahsedilen işletmelerden iş süreçleri için veri analiz sistemlerini kullanan çalışanlardan veriler toplanmıştır. Her bir organizasyondaki hedef grubun boyutları farklıdır ve şirketin büyüklüğünden bağımsızdır. Bir örnekleme yöntemi olarak "amaçlı örnekleme" seçilmiştir. Amaçlı örnekleme yöntemi, araştırmanın amacı ve içeriği sınırlı sayıda insanla tasarlandığında etkili bir yöntemdir (Dudovskiy, 2018). Türkiye'de, iş süreçlerinde veri analizini kullanan çok az kuruluş bulunmaktadır. Ayrıca, bu sınırlı sayıdaki organizasyonlar içerisinde bu sistemleri kullanan çok az sayıda çalışan bulunmaktadır. Bu nedenle, bu özellikteki belirli sayıda kişiye ulaşmak, yalnızca amaçlı örnekleme yöntemiyle ve daha spesifik olarak "uzman örnekleme" yöntemi ile mümkündür. Adından da anlaşılacağı gibi, uzman örnekleme belirli bir alandaki uzmanları hedefleyen bir yöntemdir (Etikan, Musa ve Alkassim, 2016). Bu çabalara dayanarak toplam 15 organizasyondan 91 katılımcıdan veri toplanmıştır.

6. Bulgular

Bu yüksek lisans tezinde, teknoloji kabul modeli üç önemli öncülün eklenmesiyle genişletilmiştir: *Örgütlerde Analitik Karar Verme Kültürü*, *Sistemin Analiz Performansı* ve *Sistemin Arayüz ve Entegrasyon Kalitesi*. Bu çalışma, hem akademiye hem de pratiğe oldukça popüler bir konuyu ele alarak katkıda bulunmaktadır.

Öncelikle, öncüller ve algı faktörleri arasındaki bağlantıyı incelemek gerekirse, bir iş analitiği sisteminin analiz performansı, kullanıcıların gereksinimlerini karşılamanın anahtarıdır (Saha, Nath ve Salehi-Sangari, 2012). Bir iş analitiği sisteminin analiz performansının alt başlıkları; analiz hızını, analiz fonksiyonlarının çeşitliliği ve içeriğini, analiz sonuçlarının güvenilirliğini ve verilerin güvenli bir şekilde saklanmasını içerir. Bu alt dallar sırasıyla incelenmiştir. Her şeyden önce, insan doğası gereği sabırsızdır. Yavaş yanıt süreleri, kullanıcıların iş analitiğini kullanımını engelleyebilir. İşletmeler, düşük performans sorunlarını ele almak için çok çeşitli performans geliştirme çabaları göstermiştir. Analiz sonuçlarını daha hızlı gösteren bir performans, genel olarak kullanıcıda olumlu tutum oluşturur ve kullanım oranını arttırır (Mansell, 2015). Alınan bilgilerin güvenilirliği önemlidir. Doğru bilgiler daha faydalı ve dolayısıyla daha değerlidir (Venkatesh ve Bala, 2008). Ayrıca, herhangi bir veri kaybı olmadan sistemdeki verileri güvenli bir şekilde saklamak, sistem kalite tasarımında çok önemli bir unsurdur. Tüm kalite göstergeleri uygun bir şekilde karşılanırsa, kullanıcılar sistemi yararlı olarak algılar ve iş analitiğinin kullanımı artar. Fakat kullanıcının bakış açısı, kullanım kolaylığı açısından farklıdır. Kullanıcıda, iyi analiz performansının sistemi karmaşıklaştırdığına yönelik bir algı oluşmaktadır. Karmaşıklık, içeriğin karmaşıklık derecesi ve bireyin sistemi kullanırken zorluğun nasıl algılandığı ile yakından ilişkilidir. Kullanıcılar, kullanımı kolaysa ve sistemi kullanmak kurum içinde karar vermeyi daha kolay hale getiriyorsa sistemi kucaklayacaklardır (Grubljesic ve Jaklic, 2015). Kısaca, kullanıcının iş analitiği sisteminin kullanımını kolay olarak algılaması sistemin kullanımına yönelik olumlu bir tutum geliştirilmesine yol açar. Sonuç olarak, iyi bir analitik performans, kullanıcının algısını "kullanımı kolay" olarak değil, "faydalı" şeklinde geliştirir. Öte yandan, kullanıcı dostu bir arayüz sistemin genel sistem kalitesini tamamlar. Kullanıcı dostu bir arayüzün, iyi organize edilmiş, basit bir şekilde tasarlanmış, görsel olarak çekici ve sistemin her parçasına hızlı ve kolay erişilebilir olması beklenmektedir. Bu durum sistemi öğrenmesi kolay ve kullanımı kolay olarak görülmesini sağlar. İlginçtir ki bu durum aynı zamanda kullanıcılar için sistemin yararlı olarak algılanmasına da yol açar. Tüm bu faktörler, kullanıcıların iş analitiği araçlarını kullanmaya istekli olmalarını ve kullanmaya devam etmelerini sağlayacak bir ortam oluşturacaktır (Saha ve diğ., 2012). Entegrasyon, iş analitiği sisteminin, hem organizasyonun içinde hem de dışındaki diğer kaynak sistemleriyle uyumluluğunu ifade eder. Bu, diğer operasyonel sistemlerden bilgi toplanmasını sağlar ve organizasyon içindeki raporlama ve analiz yeteneğini zenginleştirir (Karahanna ve diğ., 1999). Sonuç olarak, daha yüksek bir arayüz ve sistemin entegrasyon kalitesi, kullanıcılar tarafından iş analitiği araçlarının yararlı ve kullanımı kolay şeklinde algılanmasını sağlar.

Analitik karar verme kültürünün, teknoloji kabul modelinin bir öncülü olarak önemli bir organizasyonel faktör olduğu keşfedilmiştir. Karar vericilerin bilgi ve analitiği kullanma tercihi, kurumda analitik karar verme kültürünün varlığından oldukça etkilenmektedir (Elam ve Leidner, 1995; Singh, Watson ve Watson, 2002). Sonuçlar analitik karar verme kültürünün hem algılanan faydayı hem de algılanan kullanım kolaylığını olumlu yönde etkilediğini göstermektedir. Sonuç olarak, bir kuruluşta analitik bir karar verme kültürü mevcutsa, iş analitiği kullanıcıları iş analitiği sistemini yararlı ve kolay olarak algılar.

Teknoloji kabul modelinin temel değişkenleri olarak algılanan fayda ve algılanan kullanım kolaylığı araştırılmıştır. Çalışanların iş yerlerinde görevlerini tamamlamak için gereken bilgiye ulaşmaları ve gerekenden fazlasını yaparak işine değer katmaları iş analitiğini kullanarak sağlanabilir (Grubljesic ve Jaklic, 2015). Göreceli avantaj, iş uygunluğu, görevleri daha hızlı yerine getirme, önemli konulara destek sağlama, işteki hakimiyeti artırma ve kısaca karar verme mekanizmasını destekleme gibi yararlılık algısı, iş analitiği kullanımına yönelik tutumu önemli ölçüde olumlu yönde etkilemektedir. Daha önce bahsedildiği gibi, karmaşıklık sorunu, kullanım yönündeki tutum üzerinde algılanan kullanım kolaylığını önemli ölçüde etkilemektedir. Bununla birlikte, Davis'in (1986) belirttiği gibi, algılanan faydanın, kolay kullanım algısından ziyade, sisteme yönelik tutum üzerinde çok daha güçlü bir etkisi vardır. Ayrıca Davis'in ilk çalışmasında (1986) ve daha fazla teknoloji kabul modeli testi araştırmasının da gösterdiği gibi, kullanıcı iş analitiği sisteminin kullanımını kolay olarak algılıyorsa, kullanıcılar için iş analitiği araçlarının yararlı olarak da algılanmasını sağlar.

Araştırma modelinin bağımlı değişkenlerinden biri olarak, bireyin tutumu, bir eylemi gerçekleştirmeye yönelik duygular, düşünceler ve eğilimler bütünüdür. Tutumlar, bireyin olumlu ya da olumsuz yönde hissetme, düşünme ya da davranma eğilimini temsil eder (Vakola ve Nikolaou, 2005). Tutum, bireyin analitik düşüncesini etkileyecektir. Bu nedenle, sistemi kullanmaya yönelik olumlu bir tutum sergileyen çalışanların iş analitiğini kullanma olasılıkları daha yüksektir (Mansell, 2015). Başka bir deyişle, analiz sonuçlarına göre, iş analitiği araçlarını kullanmaya yönelik olumlu bir tutum, iş süreçlerinde iş analitiği araçlarının daha yüksek düzeyde kullanılmasına yol açmaktadır.

Kontrol değişkenlerinin iş analitiğinin fiili kullanımı üzerindeki etkisini incelemek amacıyla, öncelikle yaş ve cinsiyet faktörü analiz edildi. Fakat yaş ve cinsiyet faktörlerinin gerçek kullanım düzeyi üzerindeki etkisi önemsiz bulunmuştur. Üçüncü olarak, kullanılan yazılımın karmaşıklık düzeyi kontrol faktörü olarak test edilmiştir. Anket sonucuna göre, iş süreçlerinde iş analitiği kullanan katılımcılar 10'dan fazla farklı iş analitiği yazılımı kullanıyor. Bazı sistemler diğerlerinden göreceli olarak daha karmaşıktır. Sistemlerin karmaşıklık düzeyinin, sistemin kullanım seviyelerini etkileyebileceği düşünülmüştür. Beklendiği gibi, sistem karmaşıklığının iş süreçlerinde iş analitiği kullanım düzeyine etkisi anlamlı olarak belirlenmiştir. Son olarak, iş analitiği kullanımına yönelik tecrübe düzeyi model üzerinde kontrol faktörü olarak analiz edildi. Analiz sonuçlarına göre, daha önce iş analitiği kullanan çalışanların benzer sistemleri daha sık kullandıklarını kanıtlıyor.

Bu sonuçlarla birlikte araştırma sorusu başarılı bir şekilde cevaplanmıştır ve bulgular, araştırma hedeflerine başarılı bir şekilde ulaşılmasını sağlayacaktır.

F. TEZ FOTOKOPİSİ İZİN FORMU

<u>ENSTİTÜ</u>

Fen Bilimleri Enstitüsü [ ]

Sosyal Bilimler Enstitüsü [x]

Uygulamalı Matematik Enstitüsü [ ]

Enformatik Enstitüsü [ ]

Deniz Bilimleri Enstitüsü [ ]

<u>YAZARIN</u>

Soyadı : Bayram
Adı : Nazlı
Bölümü : İşletme

<u>TEZİN ADI</u> (İngilizce) : Examining the Use of Business Analytics in Organizations: An Extension of the Technology Acceptance Model

<u>TEZİN TÜRÜ</u>: Yüksek Lisans [x] Doktora [ ]

1. Tezimin tamamından kaynak gösterilmek şartıyla fotokopi alınabilir. [ ]
2. Tezimin içindekiler sayfası, özet, indeks sayfalarından ve/veya bir bölümünden kaynak gösterilmek şartıyla fotokopi alınabilir. [ ]
3. Tezimden bir (1) yıl süreyle fotokopi alınamaz. [x]

<u>TEZİN KÜTÜPHANEYE TESLİM TARİHİ</u>: