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Big Data Technology Acceptance in the Healthcare Industry

By

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Dedication

This thesis is dedicated to my parents, Jamal and Iman, who were my support system through this graduate program. I am truly thankful for all the love and encouragement they give me in everything I plan to do in life. Also, I would like to thank my manager, Abir Ktaich, who was very supportive and understanding to my decision in joining the program. I am blessed to have such people who believe in my career path.

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Big Data Technology Acceptance in the Healthcare Industry

Hala Chmaissani

ABSTRACT

With the advancement in information technology, researchers are realizing the remarkable potentials that big data technology can bring to the healthcare field by enhancing the efficiency of its workflow. Big data is suggested to play an essential role in the progression of the healthcare field as it provides tools to collect, organize, and analyze large structured or unstructured volumes of data. This gathered data can help in decision making. It has been contributing in the process of health care delivery and the discovery of specific diseases. Despite that, not all healthcare institutions are utilizing big data technology in their operations. This study is conducted to understand the acceptance of big data technology by healthcare institutions such as hospitals, laboratories, and medical equipment companies operating in emerging countries versus developed countries. While consonance on the importance of big data exists, results show that perceptions and attitudes toward big data usage are driven by different factors across countries.

Keywords: Big Data, Information technology, Perceived usefulness, Perceived ease of use, Healthcare, Technology acceptance model (TAM), Attitude, Behavioral intention.

TABLE OF CONTENTS

Chapter **Page**

LIST OF TABLES

LIST OF FIGURES

Chapter One

Introduction

Healthcare delivery is the base of a rigid government and the base to build a good economy. The healthcare field is one of the prominent sectors that contributes to a huge part of the governmental economy. It is one of the fastest and most growing fields in the world. However, the world population is growing every day, so the need of healthcare delivery must adjust accordingly to match this increase. Healthcare sector is very challenging as it is in continuous change and evolvement, while new diseases rise every day and require advanced observations and treatments. For this, it is crucial to keep the health sector well developed to maintain high quality services. There is a necessity for coming up with new ways to enhance healthcare delivery through increasing the job performance of the employees (practitioners, nurses, technicians, consultants…etc.) as well as maintaining the appropriate delivery of the healthcare services.

This study examines the acceptance of big data in the healthcare sectors as a mean to improve this field in its various areas, hence ensuring a more efficient healthcare field. Specifically, this study tests the behavioral intentions of users regarding big data in healthcare firms in two different countries: India versus United States. The comparison between developing (emerging) and developed countries focuses on the diversity of healthcare delivery in their firms.

Chapter Two

Literature Review

Data is the main pool of information to any company that can support it with all needed evidences and tools to function normally and improve its employees' job performances. Before, companies used to struggle to collect and backup data in a specific place to get back to it whenever needed regarding products, services, employees, and customers. They used to archive their information using basic strategies such as folders and reports, but this was always limiting their storage and data retrieval capabilities. It was not easy at all to deal with the process of data collection since it contained many complexities. In addition, the data needed a huge computing space to keep all the required data backed up in one place (Erevelles, Fukawa, & Swayne, 2016).

According to Fan, Lau, and Zhao (2015), after the technology revolution, a new data base was established that left a great impact on our daily life. This data base is just beyond technology's ability to store, manage and process efficiently. Big data was formulated, not just to store data in a given system, rather to benefit from it through extracting significant information based on the firm's interests and preferences.

By definition, big data is commonly assigned to vast amount of data that is generated, organized, and made available on different platforms to take advantage of (Constantiou & Kallinikos, 2015). It is a term for massive data sets having large, varied and complex structure with difficulties of storing, analyzing and visualizing for further processes or results (Sagiroglu & Sinanc, 2013).

Data comes from different sources, whether from companies, government, third parties, etc. Also, researches gather data through various methods, such as interviews, surveys, focus groups, archives, and observations (Fan et al., 2015). Data can be recorded down based on every single action done during a daily routine at the company. Now the tricky part is how to connect all this information together to make use of this database that otherwise it would be time consuming and waste of asset to have a bulk of unused data.

For effective use of big data, it is necessary to collect information that comes from different sources (e.g., clients, patients, suppliers, doctors…), yet share similar preferences and reacts to precise marketing indicators (Fan et al., 2015). For this, information found in the database of companies should be organized according to the preference of the company. Customer segmentation is one of the ways that aids in narrowing down collected data and extract valuable materials. Also, product or service segmentation is another method to establish proper data to increase the company's profit.

"Big Data used to be a technical problem, now it's a business opportunity" (Russom, 2011, p. 12). Over the past two decades, the interest in the field of big data has arisen due to the enormous technological developments that have evolved in our lives; especially, after the companies started data production more than they are able to extract, analyze and make use of big data. It has become a stressed matter in management, information system and social science research (Constantiou & Kallinikos, 2015).

Therefore, users have established ways to make use of this huge amount of data produced. The decisions taken in a specific market place is directly affected by the scale of the generated data, the momentum of data production, and the diverse content of it (Erevelles et al., 2016). One scale is to consider the main components of primary data which are the volume, velocity, and variety to formulate the so-called big data revolution (Erevelles et al., 2016).

2.1 Three Components of Big Data

The volume of any matter is the amount it occupies. Incredibly, after the tremendous generation of big data, scientists were astounded by the tremendous volume of big data they are receiving to a level they faced a scalability problem (Russom, 2011). Later, they created new scale units to measure big data which is the different scale of bytes (petabyte, exabytes or zettabytes). It shows the massive amount of data flowing into companies such as Walmart, Amazon, and eBay. Every day, millions of data drift into the database of the firm through various means for example, emails, phone calls, reports, tasks, etc. This large volume of data should be scrutinized to tap into new approaches in the firm and unveil new analytical strategies. On the contrary, the limited mental capabilities of humans pose some obstacles when it comes to decoding and examining a specific consumer behavior in a new environment. Thus, the critical point is the analysis techniques that should be used to handle this bulk of data. The other factor considered while measuring big data is the persistent rapidity of data creation with time. It is difficult to control the speed of collection of this data, since each person is a walking data producer. Accordingly, a very huge amount of data is collected within seconds. This characteristic is not only limited to the speed of data entry, but also to the inflow and analysis of this data to the company's database. Many traditional systems that are there in the firms are not able to engulf, process, and analyze this bulk amount of data easily. Decisions taken based on data collected from different perspectives are usually more precise than those taken based on a research or intuition (Erevelles et al., 2016). Therefore, big data should be used since it is produced to increase the organization's value (Sagiroglu & Sinanc, 2013).

This dimension explains the big data terminology. There are millions of different resources that data comes from, so data can be categorized into many groups according to either organization, type, or randomly. It can come from an email message, personal information on social media, or GPS signals on cellphones. "Big data comes from a great variety of sources and generally comes in three types: structured, semi-structured, and unstructured" (Sagiroglu & Sinanc, 2013). Structured data forms are already segmented and can be easily sorted into the firm's database. As for the unstructured forms are usually uncategorized and much harder to analyze and extract data from. Semi-structured data contain valuable material but requires a bit of effort to sort it out (Katal, Wazid, & Goudar, 2013). Consequently, this diversified amount of data that is generated from a certain organization should be grouped in a unified programming interface to improve access efficiency and development and reduce system complexity (Zhang, Qiu, Tsai, Hassan, & Alamri, 2017).

A wide variation in data collection is very critical as it has to abide by some checkpoints in order to be effective. All these data sets have a steadily declining cost according to their date of collection; therefore, it is serious which data to choose according to its date of collection. Moreover, the relevance of the data to the field of work is important to aid the organization in boosting their performance and increasing profit (Katal et al., 2013).

2.2 Theoretical Framework

2.2.1 Factors

Big data aligned with technology can be measured by different factors. One of the models used to study the adoption of big data is the technology acceptance model (TAM). TAM was first developed by Davis in 1989, then he, along with other researchers, scaffolded on this model to create several versions of it. This model tries to clarify and expect why users sometimes agree and sometimes refuse information systems (IS) (Lai, 2017). TAM shows what specific factors influence the decision of users when they are subjected to a new technology especially on how and why they will use it (Ahlan & Ahmad, 2014). “TAM has become well-established as a robust, powerful and parsimonious model for predicting user acceptance” (Venkatesh, & Davis, 2000, p. 187).

Later on, the TAM model was extended to TAM2 to include extra key determinants that might affect the main factors of it which are perceived usefulness and ease of use. These additional theoretical antecedents create bridging social influence processes which are the subjective norm, perceived behavioral control, and technology training. These forces impose an impact on the consumer’s opportunity to accept or reject big data (Venkatesh, & Davis, 2000). After TAM2, Davis scaffolded on this model to include different factors and consider several external variables. However, TAM2 model was applied to conduct this study.

According to this model, the acceptance of big data can be measured by its perceived usefulness, perceived ease of use, and user acceptance through valid scales (Adams, Nelson, & Todd, 1992). The main concept of this theory is centered on the increase the use of information technology by endorsing its acceptance. This theory can be tailored to deliberate the effectiveness of big data in a specific field/business. Measured scales vary between direct and indirect determinants that are evaluated to assess the final acceptance of big data.

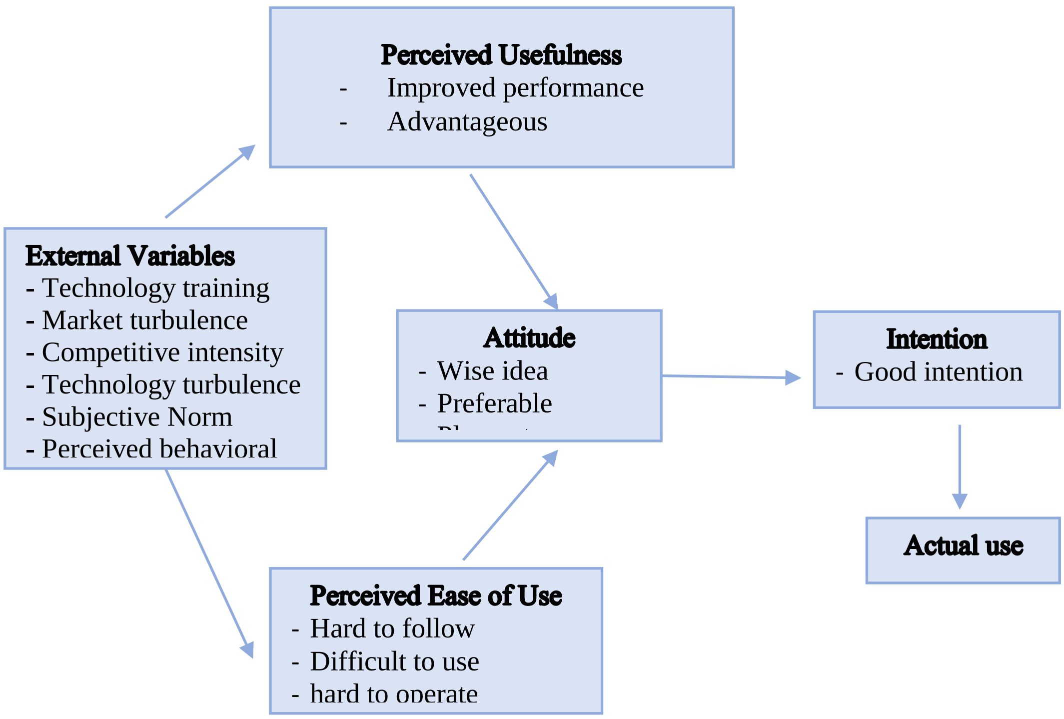

Figure 1. Overall Technology Acceptance Model (TAM)

Perceived usefulness: Is the level to which a person sees big data as a helpful tool in his field of work. Adoption of innovations depends prominently on the perceived usefulness of the consumers (Adams et al., 1992). If the employee believes that there is a good and motivational performance regarding big data, this implies that big data is a beneficial tool in the organization. On the contrary, if the employee foresees big data as a useless junk of information that might not increase the profit of the organization, this implies that big data is an unbeneficial tool in the organization. Therefore, employees tend to use or not use a new system application to the level they believe it will help them accomplish their jobs better (Davis, 1989).

Hence, users of big data should go through scale items to assess their behavioral intentions toward this system. As such, the company will decide on installing big data after this assessment.

Perceived usefulness can be assessed according to scale items. The results can be categorized into three main bunches. The first bunch of items includes the job efficiency, the second bunch is concerned with time saving and productivity, and the third bunch is related to the importance of the system to the workflow (Davis, 1989).

Perceived ease of use: It is the level of ease that the person sees big data. One might consider it a hard tool to understand and use, while other might see it very easy. This tool highly influences the implementation’s success or failure depending on the practitioner’s willingness to learn new ideas and routines. Some employees might consider that a given application is useful but at the same time too hard to understand and the benefits of using this system is outweighed by the efforts exerted to understand this system (Davis, 1989).

As technology evolved over the last decade, studies have displayed that consumers showed an increased level of ease of use to various introduced technologies (Tirunillai & Tellis, 2014). Now, employees are more prone to accept new information technologies introduced in their firms as they are getting exposed to various technologies in their daily life.

Consequently, employees shifted to be more concerned about the utility of information technology rather than its complexity, since the concept of introducing technology in different aspects of the organization is getting familiar. This indicates that as employees gain experience in the usage of big data, ease of use is surpassed by other aspects (King & He, 2006).
With the increased interest of information technology in all industries, the healthcare sectors are aware of importance of this IT in improving their workflow. New healthcare IT systems are at risk of failure if the utility is not carefully introduced and grasped (Jones et al, 2012). A proper introduction of the new system must be done to the employees who are displaying ability and willingness to learn new strategies and structures of the organization's workflow.

User acceptance: Is the level to which the user can engulf this new concept and consider it in his work. It is true that technology has enhanced our way of living in all sorts, yet many still find it very hard to adapt in their daily life. Same goes to big data, it might be a challenge to adopt to such an innovation in a short period of time. Acceptance is hypothesized through the psychological process that users pass through in making their decisions when it comes to big data (Dillon & Morris, 1996).

The advantage of big data in the organization can be only sensed when the employees of this firm indorse it. User acceptance can be improved through many ways. Many researchers believe that the challenges to user acceptance is the lack of approachability of system installed. Though the ease of use of the system is very essential to accept big data, yet the value of its function should not be disregarded (Davis, 1993). Employees should have enough willingness and ability to tolerate the difficulty of the installed new system that will help them in their job. Therefore, the proper assessment of user acceptance is to present a prior design that will give an overall view of the final implementation of big data. The tests performed in the early stages of design could diminish the possibility of user dismissal through permitting designers to better screen, arrange and upgrade application concepts (Davis, 1993).

One process to apply this design is to provide users with a prototype of the application, allowing them to get introduced to it and interact with it. After that, designers measure the users' performances, then collect their evaluations and feedbacks and adjust the design correspondingly. Another process is to demonstrate a simulation video of the application to employees and get back their assessments right away.

Also, age plays an important role in accepting new inventions, and making it part of the daily routine. The influence of age on user acceptance is crucial in the integration of big data in an organization. As people get older, they tend to require more assistance in accepting this information technology. Age affects in the ability, approach, performance and willingness to use new technologies. For instance, older employees tend to show negative approaches and are less relaxed with big date because of less experience, in comparison with younger employees (Kuo et al, 2009).

2.2.2 Antecedents

In this research, the measurement of social influence factors is incorporated as antecedents to increase the predictive power of the TAM2 model. These factors would give a depth in the analysis of the results and provide a clearer understanding of big data in healthcare field.

Subjective norm: It is the social pressure that can affect a person’s perception towards a specific task and hence influence his performance (Venkatesh & Davis, 2000). In the primitive TAM model, subjective norm is not measured. However, during the evolution of the TAM, it is modified to TAM2 model by Venkatesh and Davis (2000), this factor is measured as a direct predeterminant for the 3 main measured elements.

According to Davis et al. (1989), subjective norm has no momentous effect on the intentions over the perceived usefulness and ease of use. Based on the results of our study, subjective norm has a more remarkable effect on the ease of use than the perceived usefulness. People tend to take on undesired tasks after they receive advices from their surroundings. The word of mouth can even push consumers to get immensely motivated to conform by the task.

Subjective norm has an indirect effect on the intention of the employee through the perceived usefulness. For instance, if a manager believes that performing a specific task is beneficial, the employee might also come to a fact that accomplishing this task would be useful. The employee would adapt his manager's belief and implement it in his work (Venkatesh & Davis, 2000). Consequently, the word of mouth highly affects the success or failure of big data in a given firm. Managers should pay attention to the 'buzz' that is running around their environment. These positive or negative vibes that each employee receives, play an important role in accepting the installed technology.

Perceived behavioral control: It is the level to which the consumer can be in control of a performed task or behavior (Ajzen, 2002). This variable was created to examine situations in which people drought complete control over significant behavior. For example, when a student applies for medical school and he submits all the required documents, it is out of his hands if the department accepts another student who is more eligible to be a doctor than him. In this case, the student has no control of the behavior or the decision taken. As a matter of fact, perceived behavioral control is better explained as "perceived control over performance of a behavior" (Ajzen, 2002).

Other behaviors can be considered in that frame but can be considered as voluntary behaviors. These types of behaviors are controllable and the student can make sure that they are in his favor to submit the application, such as GPA, MCAT, interview…etc. nevertheless, there are some unforeseen circumstances that come through the individual's path, and therefore the volitional control over these types of behaviors varies accordingly (Ajzen, 2002). As the person's perceived control increases, it strengthens his intention to perform the behavior, hence increasing persistence and performance. In reference to the survey done, perceived behavioral control has a positive effect on the perceived usefulness of big data in a given organization.

The combination of the subjective norm and the perceived behavioral control gives rise to the actual attitude and primes to the creation of behavioral intention to do a task.

Technology Training: It is the appropriate guidance that the employee gets to further grasp the newly implemented system and enhance the quality of work. Managers assure that each employee clearly understands the user manual, features, and the overall structure of the system to be able to use it in performing his job tasks more efficiently, hence increasing the organizational profit. It is necessary to deliver a proper user training for guiding and hardening the user's vision of the usefulness of the technology in his field of work (Hu, Chau, Sheng, & Tam, 1999).

Therefore, the firm should support the installation of big data with a large training program in addition to a referent assistant desk (King & He, 2006). The training should start with demonstrating the importance of emerging big data in the organization's workflow and show ease of use and usefulness of it. Then, informational sessions and trainings about the structure and the application of big data in the current system will follow to assure the right implementation of this system in the firm and make use of it.

2.3 Big Data in Healthcare Field

2.3.1 Health Care Industry Overview

In most countries, the healthcare industry contributes to its economy with a remarkable percentage. For example, in 2016, the total healthcare expenditures in the U.S. stood at $3.3 trillion (Blazheski & Karp, 2018). If this trend remains as it is in the future, the continuous increase of the cost of healthcare will remain accumulative to reach 23% of GDP by 2030 (Blazheski & Karp, 2018). Healthcare sector varies to include pharmaceutical companies, medical equipment suppliers and distributers, hospitals, and laboratories.

A good healthcare industry is dynamic. It reflects a healthy population that has the total ability to treat illnesses and hence, would decrease financial loads due to reliable labor force. On the contrary, a bad healthcare industry would reflect a bad economy, and in return this would result in bad health. For example, in Sierra Leon, 4000 people died from E. bola virus. This is best explained by the poor economy that Sierra Leone suffers from, which reflects less funding into the health sector. Therefore, it is a connected cycle by which the economy of the country and the health sector hold up each other (Simion, 2017). This industry contributes to the world's economy in a huge percentage, and so to have a good economy, the country would need to establish a worthy healthcare sector.

Decades ago, Toffler and Alvin, wrote a book entitled "The Third Wave". This book predicted the transformation of societies from the industrial age, which he called the second wave, to the information age, the third wave. Consistent with the same point, Toffler and Alvin illustrated the importance of technology and data as two powerful factors in facilitating changes in society (Toffler & Avlin, 1980). From this, big data can be considered as a very essential tool to enhance healthcare fields and assist the work of practitioners and employees in different aspects. Though many researches are considering the potential benefits of big data implementation in healthcare sectors, yet till date none of them had pushed these studies further to apply it in their systems (Wang, Kung, & Byrd, 2018).

However, healthcare sector is facing a lot of challenges in recent times. Some of the vital challenges are the high cost of care services, increase patients' volumes with affordable care act, increase of chronic diseases, and penalties for relapsing and substantial reductions in reimbursement (Nambiar, Bhardwaj, Sethi, & Vargheese, 2013).

Researchers try to restructure healthcare to enhance the quality of care delivered and get an efficient system that yields in high profit. Major healthcare changes are being discussed around the world. Some of these changes are:

- Increasing, safety, quality, efficiency, and decreasing health discrepancies
- Enlightening care coordination and public health
- Preserving the security and privacy of patient health information

- Enhancing medical results
- Increasing efficiency and transparency
- Producing forceful research data on health systems (Nambiar et al., 2013).

Meanwhile, these services can be improved using various ways of information technology infrastructures. These alterations can be accomplished through the administration of information technology, i.e. big data, into the healthcare field.

The analysis of big data plays an important role through collecting enough information at the point of care to permit faster, safer, and more proficient medical practices. The vast amount of data collected and organized digitally have created a science of data management. Therefore, this incredible load of big data can contribute to the achievement of the firm’s objectives and their stability.

Big data is a new innovation that is becoming the trend in both science and business field. Consequently, it should be monitored to evaluate its impact on various fields. It has a noticeable potential to organize and grow healthcare managers and employees as a mean to increase quality and proficiency of healthcare delivery (Murdoch & Detsky, 2013).

This vast volume of data flowing into the hospital each day can be analyzed to give the practitioners a better chance to understand symptoms, causes, and even cure of a certain disease. It is being collected from every entry record at the hospital starting from the consumable devices, doctors, nurses, patients, to clinics and surgeries. This implies a big variety in the type of data collected in a single day. The hospital can have a high extent of data coming from different departments. Therefore, they can be categorized into separate classes depending on their benefit. Consequently, this data requires a high-speed system to respond to this data and store it properly, so big data is assessed by an increased velocity that is able to grasp massive data flowing in.

Several pathophysiological and clinical symptoms contribute to the assessment of various diseases. Along with different systems within the body that may interact and lead to specific clinical assessment. Therefore, the link between our body systems and the prediction of probable diseases require collection of huge data of clinical history and analyzing them to get the likely disease and its state. Researchers are integrating big data analytics in the healthcare field to better understand the human physiological and pathophysiological aspects (Belle et al., 2015).

Big data is an information system that is able to generate significant information from a daily routine at the hospital which might be beneficial in different departments. Its adoption is affected by those employees in the firm who are primarily using the implemented technology (Jensen & Aanestad, 2007).

2.3.2 Examples of Information Technology in Lebanese Healthcare Firms

For instance, in 2018, the American University of Beirut Medical Center (AUBMC) which is one of the leading hospitals in Lebanon launched AUBHealth. It was developed by Epic. It is a platform that provides an integrated care for patients to ensure convenient digital access to their health information (“AUBMC launches AUBHealth, a new comprehensive health record system”, 2018). This system allows patients to connect with their healthcare sources, arrange appointments, and get their test results easily. On the other hand, all healthcare providers received proper trainings to deal with this electronic medical records to be able to submit their work in different departments of the hospital such as laboratory, radiology, pharmacy, blood bank, and even billing ("AUBMC launches AUBHealth, a new comprehensive health record system", 2018).

Moreover, Hotel Dieu De France, which is another leading hospital in Lebanon has celebrated the launching of a new hospital information system (HIS), the DxCare. In 2018, this system was finalized to optimize the hospital's internal process and guarantee patient safety in the first place. DxCare ensures tracking patient progress from entry until discharge, tailoring healthcare based on patient needs, and automating and linking all subordinate departments to the concentrated widespread HIS ("Hôtel-Dieu de France Digital Transformation Led By ITG", 2018).

According to one of the dominant acceptance models, technology acceptance model, there are three factors that measure the level of tolerance of the introduced technology to a firm. User's perception, acceptance, and ease of use can determine the level of success of the implemented system. When TAM is applied in healthcare firms, it shows the importance of performance expectancy, which reflects the level of healthcare workers belief in using technology to increase job performance.

2.3.3 Advantages and Disadvantages

Even though the healthcare field requires elevated level of expertise, it is highly routinized, and it is clearly shown in the process done to deliver the right service of care. Therefore, big data can be integrated in healthcare systems in the daily routines of doctors, nurses, and technicians to increase performance and quality. However, there are antecedent that are considered in the assessment of the degree of acceptance of the big data in the healthcare field. According to a study done in Greek health sector, a positive relationship resulted between the attitude of medical staffs and behavioral intention. Also, some additional external variables were studied such as age, gender, specialty, and hours of using a computer per week. These factors had an effect on the acceptance of the clinical information system among hospital (Melas, Zampetakis, Dimopoulou, & Moustakis, 2011).

Technology is a tool that helps in organizing and structuring systems, yet it is not easy to implement such gears and get along right away. It can take a bit of time before it is implemented totally in the daily routine of the specialists. Big data application failure can be easily related to practitioners' obstruction with the systems' functionality and the trouble they might have faced in assimilating the technology into their workflow. In addition, this failure might be linked to the unwillingness of the physicians to value and accept the makeover and restructure of the organization. According to the Hersey and Blanchard (2007), the ability and the willingness of the employee are two important factors to assess the readiness to do his job duties properly, hence getting a corresponding reaction from his manager. Consequently, when tailoring this theory to the application of big data in the healthcare industry, the staff should have enough ability and willingness to grasp new information technology and be ready to use it accurately.

On the other side, a successful implementation of information technology is highly associated with the perception and the adoption of the healthcare professionals who are the primary users of this system. Such accepting user will be open for this remarkable shifting in the organization and might even enjoy learning the new system and the independency of the organization (Jensen & Aanestad, 2007).

Chapter Three

Hypothetical Development

Subjective norm is the effect of the environmental opinion on an individual's behavioral activity toward a specific given task. In any healthcare organization, the social pressure toward any idea, belief, objective, or task play a role in the final perception of the co-workers. This antecedent is measured to evaluate its effect on the two factors in the TAM2 model; perceived usefulness and ease of use. An employee would recognize the significance of big data in his work due to outside buzzes, same as another employee in the same healthcare firm who would recognize it as worthless due to word of mouth. Therefore, subjective norm plays an important role on the perceived usefulness of big data. Moreover, this factor has a greater effect on the ease of use of big data.

In consistence with the theory of reasoned action (TRA) that was developed by Fishbein and Ajzen (1975), subjective norm is a direct determinant of behavioral intention in that model. As people get positively affected by the surrounding about a specific task, they will perceive this task as a very useful one to consider. Also, they will learn this task and even know how to manage this task easily. Consequently, they will formulate a positive attitude towards it, hence a positive behavioral intention is made. Perceived usefulness and ease of use of the user can be assessed through in relation to one of the dominant antecedents, subjective norm. As such, the below hypotheses are anticipated.

H1.a Subjective norms has a positive effect on perceived usefulness.

H1.b Subjective norms has a positive effect on ease of use.

When a new systematic structure such as big data, is introduced to an organization, all users should undergo an effective training in order to have the new system built in their daily routine. This would allow them to get familiarized with the installed system and understand its mechanism. Technology training is even more essential to employees because it breaks down the habitual tasks that they perform each day and restructure it to comply with the new standards. Trainers should emphasize the value of big data on attaining the final objective of the company with higher efficiency and productivity.

As employees become acquainted with big data in their firm, as a result their ease of use toward this system would increase. This shows a higher acceptance to big data through the users' behavioral intentions regarding this installation. Technical support such as training programs and consultative assistance has a solid and direct correlation with perceived usefulness of the system and the perceived ease of use (Wu, Wang, & Lin, 2007). Hence, the below hypotheses are anticipated.

H2.a Technology training has a positive effect on perceived usefulness.

H2.b Technology training has a positive effect on ease of use.

According to the theory of planned behavior, it scaffolded on the TAM models to include conditions where individuals are not in complete control over their behavior (Taylor & Todd, 1995). For this, perceived behavioral control was considered to measure the variation of perceived usefulness and ease of use. Perceived behavioral control is the user's belief in his ability to have control over specific given task that effects his life (Ajzen, 2002). For example, an employee might believe that using big data is out of control, consequently he will lose the importance of big data usefulness and how it is used (Taylor, & Todd, 1995). In the healthcare sector, whenever the staff believes that they are able to manage big data, they will perceive its usefulness. When the user is in charge of the objectives given to him, he will be able to understand the benefits of these objectives better. Moreover, he will find it easier to handle the system and deal with it as he will be able to tailor the system according to his own desires.

Thus, the main factors of the technology acceptance model are directly affected by the perceived behavioral control which indirectly affects the behavioral intentions. Therefore, the below hypotheses are anticipated.

H3.a Perceived behavioral control has a positive effect on perceived usefulness.

H3.b Perceived behavioral control has a positive effect on ease of use.

Perceived usefulness is defined previously as the user's tendency to evaluate the importance of technology information implemented in the healthcare firm. As practitioners value the importance of using big data in the hospital, their attitude towards it would be positive, hence they would be more prone to accepting it as part of the organizational structure and working with it to enhance their final outcome in helping patients.

Perceived usefulness is the organism that represents the motivation to use the system that leads to consumers' respond to use the system (Lai, 2017). Therefore, as the user gets aware of the importance of the new system in use, a positive attitude will be created towards this system. Perceived usefulness has a direct influence on the attitude of the user (Wu, Wang, & Lin, 2007). Likewise, TAM model suggests that perceived usefulness is one of the central determinants along with the ease of use in affecting the employee's attitude (Schepers & Wetzels, 2007). Hence, the below hypothesis is anticipated.

H4. Perceived usefulness has a positive effect on attitude towards big data

According to the theoretical extension of the technology acceptance model (TAM2) by Venkatesh and Davis (2000), the perceived ease of use is recognized as the level to which a user believes that using the installed system will be free of effort. Ease of use is another determinant measure to evaluate the attitude of the nurses, practitioners, and technicians in a given hospital. As big data is observed as an easy system to handle while entering data, organizing information, or delivering results to patients, users would form a positive attitude regarding big data. Even though one might observe big data as a very beneficial tool to implement within a system, yet he might consider it very hard to grasp and handle. Therefore, it is very critical to the trainers to use an effective presentation to demonstrate big data as a helpful yet an easy tool to use.

When a big data is implemented in a corporation, it is essential to monitor the perceived ease of use of the staff and managers. As they are the end users who will be using this system to increase productivity and performance of the company, trainers need to emphasize on the effortlessness use of the system though it is a very complex one. Once users perceive big data as an easy tool to handle during their daily routine, they will express a positive attitude toward using it. Also, they will be motivated to develop the way they perform their job objectives.

This means that the employee’s perception of the level to which an installed system is easy to use heavily affects the attitude of this employee regarding the system. Thus, attitude is developed through the measurement of perceived usefulness and ease of use combined (Taylor & Todd, 1995). As such, the below hypothesis is anticipated.

H5. Ease of use has a positive effect on attitude.

According to the TAM model, behavioral intention is an important element of information technology usage behavior, hence it is crucial to investigate the primary and secondary factors that might affect this element (Taylor & Todd, 1995). In general, individuals behavioral intention is highly influenced by the perceived usefulness and the perceived ease of use (King & He, 2006). On the contrary, in TAM, the primary effect of perceived usefulness on the behavioral intention is significant, yet attitude does not show a significant influence on behavioral intention (Taylor & Todd, 1995). This is explained due to the presence of other factors in the workplace settings such as perceived usefulness and ease of use (Davis, 1989). However, this chain of relations is mediated by the attitude formulated regarding the applied information technology. Whenever the user creates a positive attitude toward big data that will be introduced into his working environment, this would lead to a confident behavioral intention in accepting, understanding, and even using this new data system in his field of work. Therefore, the below hypothesis is anticipated.

H6. Attitude has a positive effect on behavioral intentions.

3.1 Research Question

After the evolution of technology, big data has become a central interest in all countries to benefit from it and enhance their workflow in all sectors. However, the world is divided into two types of countries, the emerging countries while the other countries belong to the developed countries. Each country has its specific healthcare system that has its own contribution to the country's economy. In the less developed countries, such as India, the healthcare sector has a poor significance on the country's economy (Simion, 2017). On the contrary, in developing countries, such as USA, healthcare sector has a remarkable effect on the country's economy. Consequently, big data acceptance in these countries will vary according to the level of advancement that their healthcare sector has achieved.

Since there are discrepancies between firms operating in different countries, one sample from each type was studied in order to include both types of countries and to have a reliable research. This leads to the research question that will the relationships hypothesized above regarding the acceptance of big data in the healthcare industry vary between developing and developed countries?

Chapter Four

Methodology

4.1 Research Framework

The goal of this thesis is to understand the attitude of healthcare firms toward big data and the possibility of incorporating it to their companies. This research is survey-based study conducted in the healthcare field. A representative sample of healthcare firms is utilized to test the hypothesized relationships. The sample constitutes executives, managers, or directors representing the different firms. The data was analyzed using partial least square – structural equation modeling using SmartPLS 3.0 (Ringle, Wende, & Becker 2015).

4.2 Sample

Data for this study was collected using a web-based survey developed through Qualtrics. Convenience sampling technique was used with a final sample size of 93 managers representing different healthcare firms that are not utilizing big data systems/technology in their operations. The focused was based on two countries (USA and India) to assess any effect of the country's economic development level. In this study, USA is considered a developed economy while India is emerging economy (Kathuria et al, 2010). The sample collected from managers working for firms operating in the USA is equal to 38, while that if managers working in India is equal to 55. Upon accepting to participate in the study, respondents were required to answer multiple checking questions to make sure they are the target of this study. For example; "*What is your job level*?" and "*In which industry the company you work for operates?"* Descriptive statistics of the respondents are summarized in table.1. Also, a definition of the terminology of big data was included in the survey to ensure that all respondents are aware of the topic they are dealing with.

Overall Sample characteristics

Variable	Category	Frequency
Age		
Gender	Male Female	54 39
School degree	High school degree High school graduate College no degree Associate degree Bachelor’s degree Masters’ degree Other	0 2 3 6 54 28 1
Country	USA India	38 55
Job level	Executive Director Manager Advisor Staff	4 6 82 1 1
Department/Work function	Production Research & development Marketing Sales Information Technology Quality Assurance Supply chain Management Service Others	7 15 8 15 18 4 11 15 1
Industry	Healthcare & pharmaceutical	93
Offering type	Service products both	23 30 40
market	B2C B2B Both	32 37 24

Table 1. Sample descriptive Statistics

4.3 Measures

Multi-item scales were adapted from prior studies to measure the constructs of interest in this study. Prior studies provide reliable and valid measures that can be used. The measures were adapted to fit the big data context since all measures were used before in different contexts (e.g., CRM technology). In addition, the survey included questions about the firm and respondents' demographics.

Technology training was measured based on four-item scale adapted from Hunter and Perreault (2007). To measure perceived behavioral control and subjective norm, multi-item scales were adapted from Taylor and Todd in 1995. The same study was utilized to adapt the measures of perceived usefulness, ease of use, attitude toward big data, and behavioral intentions toward adapting big data.

To control for some of the differences between the healthcare firms the respondents work for, brand equity and offerings quality were included into the model as control variables. Firm (brand) equity was measured based on three-item scale developed by Verhoef, Langerak, and Donkers (2007). Quality of the firms' offering was adapted from Fombrun, Gardberg, and Sever (2000). The links from both control variables to attitude and behavioral intentions were included in the model. All the items were measured based on agreement Likert scale (1 = strongly disagree; 7 = strongly agree) except for quality that was measured based on the following scale point (1= much worse; 7 = much better).

4.4 Measurement Model

The measures were first checked for reliability and validity. The outer model was tested in Smart-PLS (3.0). The measures used achieved satisfactory levels of reliability of lowest composite reliability equals to 0.80 of technology training and behavioral intentions constructs. The items loaded significantly ($p < 0.01$) on the factors they were assigned to. No problematic cross loading was found. This provide evidence of convergent reliability (Anderson & Gerbing, 1988). Discriminant validity was checked based on the procedures recommended by Fornell and Larcker (1981) in which inter-correlations of all pair of variables were compared with the square root average variance extracted (table.2). Only few pairs of comparison were greater that the square root average variance extracted. Furthermore, the lowest average variance extracted was equal to (0.507). No evidence of collinearity was found with variance inflation factor (VIF) range between (1.2) and (2.14). The measures possess satisfactory evidence of reliability and validity.

Measurements	Loadings
Technology Training CR: 0.8044, AVE= 0.5071	
I have had effective training on technology tools.	0.744
My technology training has been "world class?'	0.695
Technology training in this firm is effective	0.694
This firm needs to revamp its technology training programs.	0.714
Attitude CR= 0.8769, AVE= 0.6409	
Using the big data is a good idea.	0.859
Using the big data is a wise idea.	0.81
I like the idea of using the big data.	0.753
Using the big data would be pleasant.	0.777
Perceived Usefulness CR= 0.8190, AVE= 0.6021	
Using the big data will improve performance.	0.717
The advantages of the big data will outweigh the disadvantages.	0.79
Overall, using big data will be advantageous.	0.817
Ease of Use CR= 0.8648, AVE=0.6813	
Using big data technologies will be hard to follow.	0.81
It will be hard to learn how to use big data technologies.	0.785
It will be hard to operate the big data technologies.	0.878
Subjective Norm CR= 0.8827, AVE=0.7900	
People who influence my behavior would think that I should use the big data technologies	0.892
People who are important to me would think that I should use the big data technologies	0.886
Perceived Behavioral Control CR= 0.8285, AVE=0.6170	
I would be able to use the big data technologies	0.76
Using the big data technologies is entirely in my control	0.784
I have the resources and the knowledge and the ability to make use of the big data technologies	0.812
Behavioral Intention CR= 0.8097, AVE= 0.5891	
I intend to use the big data technologies as soon as it is implemented.	0.745
I intend to use the big data technologies.	0.87
Once big data technologies are adopted by my company, I intend to use it regularly.	0.675
Brand equity CR= 0.8510, AVE=0.6590	
Our company's brand is a strong brand.	0.893
Our company's brand is a well-known brand.	0.669
Our company's brand is a unique brand.	0.855

Table 2. Data Analysis: Measurement, Cronbach's Alpha, Composite Reliability, AVE, and Items Loading

4.5 Results

The results were based on the inner model analyzed in Smart-PLS (3.0) in which standardized beta-coefficients were extracted with their significance level using bootstrap technique. In this study, three antecedents of perceived usefulness and ease of use were hypothesized. The overall model results show subjective norm to positively affect ease of use (B = .411, $p < 0.01$). The results also show a positive effect of perceived behavioral control on perceived usefulness (B = 0.595, $p < 0.01$). The results thus support H1b & H3a. The other relationships hypothesized were not statistically supported. The percentage of variance explained for perceived usefulness is 52.5% and that for ease of use is 25.7%.

In hypotheses 4 and 5, positive effects of perceived usefulness and ease of use on attitude of using big data technology are hypothesized. The results are in support of both relationships with perceived usefulness (B = 0.717, $p < 0.01$) and ease of use (B = 0.241, $p < 0.01$) driving favorable attitude toward big data technology. In turn, the positive attitude is suggested drive behavioral intentions toward the usage of big data technology (B = 0.655, $p < 0.01$). Only quality holds significant effect on behavioral intentions (B = 0.213, $p < 0.05$), suggesting that the higher the offerings quality of a firm the more intentions of its representative regarding the future use of big data technology. The percentage of variance explained for attitude toward big data technology is 73.8%. The percentage of variance explained for behavioral intentions is 48.3%.

The research enquiry included in this thesis questions the possible effect of country economic development level on the relationships found in this study. For that, multi-group analysis was conducted by splitting the sample used in this study based on the country (India versus USA). The relationships hypothesized were then tested and compared. The multi-group analysis is included in table.3.

	AT	**EoU**	**PU**	**PBC**	**TT**
Attitude (AT)	*0.8005*				
Ease of Use (EoU)	0.3372	*0.8254*			
Perceived Usefulness (PU)	0.8174	0.1290	*0.7759*		
Perceived Behavioral Control (PBC)	0.6852	0.3652	0.7118	*0.7855*	
Technology Training (TT)	0.6303	0.3545	0.5126	0.5835	*0.7121*
Behavioral intentions (BI)	0.6813	0.3551	0.6846	0.7865	0.5251
Brand equity (BE)	0.5866	0.2356	0.5483	0.4825	0.7411
Quality (Qual)	0.5410	0.2581	0.5519	0.5267	0.6472
Subjective norm (SN)	0.5776	0.4974	0.5050	0.5930	0.6003
Overall Sample					
Mean	5.19	4.91	5.33	5.17	5.18
Standard Deviation	1.01	1.13	0.97	0.94	0.90
USA sample					
	4.79	4.57	5.08	4.95	4.87
	1.15	1.20	1.15	0.99	0.95
India Sample					
	5.45	5.14	5.49	5.31	5.39
	0.81	1.02	0.79	0.88	0.81
Mean difference between two samples	.65	.56	.40	.35	.51
T-test of the significance of the mean difference	3.03^{**}	2.36^{**}	1.89^{*}	1.79^{*}	2.71^{**}

	BI	BE	Qual	SN
Attitude (AT)				
Ease of Use (EoU)				
Perceived Usefulness (PU)				
Perceived Behavioral Control (PBC)				
Technology Training (TT)				
Behavioral intentions (BI)	*0.7675*			
Brand equity (BE)	0.3921	*0.8118*		
Quality (Qual)	0.4533	0.7512	*0.7712*	
Subjective norm (SN)	0.6807	0.5073	0.5445	*0.8888*
Overall Sample				
Mean	5.32	5.47	5.55	5.18
Standard Deviation	0.86	1.02	0.88	1.08
USA sample				
	5.12	5.12	5.30	4.86
	0.93	1.16	0.97	1.29
India Sample				
	5.45	5.70	5.72	5.40
	0.80	0.85	0.78	0.86
Mean difference between two samples	.33	.58	.42	.53
T-test of the significance of the mean difference	1.78^{*}	2.63^{**}	2.21^{**}	2.21^{**}

*Table 3. Correlations Matrix * p<0.1; ** p<0.05*

The results show that positive perceived usefulness effect on attitude toward big data technology is stronger in developed economy (USA) compared to emerging economy (India) ($B_{USA} = 0.85$, $p < 0.01$ versus $B_{India} = 0.46$, $p < 0.01$, Δ $p < 0.1$). While the overall model results show subjective norm to positively affect ease of use ($B = .411$, $p < 0.01$), the multi-group analysis demonstrates that this relationship only holds in developed economy since it is not significant in emerging economy ($B_{USA} = 0.61$, $p < 0.01$ versus $B_{India} = 0.12$, $p > 0.1$, Δ $p < 0.05$).

4.5 Discussion:

This research talks about the effect of big data implementation in the healthcare field. The effectiveness of big data is measured using the TAM model, with its different variables. Outcomes that resulted from the survey highlight on some of the relationships of the factors of the TAM model. When comparing the results between India and USA, positive effect of subjective norm on the ease of use as significant only in USA. This shows that employees in developed countries are more prone to respond to their surrounding than those in developing countries. Further, the outcomes supported the positive effect of perceived usefulness and ease of use on the employee's attitude. Employees will more likely accept the application of big data in a given organization only if they are able to consider it as a valuable and easy tool to be used to increase productivity and profitability. This study tackles the big data topic from the healthcare perspectives. Hospitals are in need of this information technology, since it would have a great impact on the efficiency in patient care delivery. The goal of any hospital is to serve their patients with the best available care in addition to improve profit margin. With the use of big data, hospitals can collect, manage, organize, and analyze records which would be beneficial in different aspects. Big data would help practitioners to look deep in a disease, connect the dots, and discover the cause behind this disease or find a cure for it. Big data would increase efficiency in the workflow of the hospital, as the staff will be able to perform their job objective more accurate, thus this would lead to a decrease in the turnaround time for healthcare delivery especially at the emergency room. As a result, more patients will be able to admit to the hospital, so the hospital's profit will increase. According to tested respondents, employees who work in healthcare firms would behave positively towards the application of big data in their firms only if they formulate a positive attitude regarding this information technology. However, as the healthcare firm presents a good quality of big data implementation, its staff will show a better behavioral intention to accept this new installed system, hence the firm will get a successful organizational upgrade.

Moreover, findings from the research proved that the correct implementation of big data in the healthcare field would be very efficient regarding productivity and effectiveness. The right installation includes the assessment of the staff's ability and willingness toward this system. Also, trainers should reveal the importance of big data on all aspects of the firm and give a proper and efficient training to its staff to be able to use the system correctly and understand its usage properly. Therefore, the process of accepting big data as a newly implemented information technology in healthcare field depends on a chain of factors and antecedents that are link together.

4.6 Limitations and future research

In this research, a small sample size was taken into consideration due to various limitations. Big data acceptance was narrowed down to be tested in the healthcare field in specific. This condition made it more challenging to collect results from available healthcare companies and get more reliable results. However, the aim of the research was to test big data in the healthcare field. Also, only two countries were considered as the reference pool of testing (USA and India) which limited the field of research during data collection. Since the topic is limited to testify the acceptance of big data in the healthcare field only, researchers must look on other aspects of limitations to improve their study. As a result, they are advised to scaffold on this study and include more countries when comparing between developed and developing countries in order to collect sufficient data that will be the base of their study.

Moreover, this research built a conclusion based on the study of healthcare industries such as hospitals, pharmaceutical companies, and medical equipment distributers only. As a result, all the tested factors and antecedents that affected the acceptance of big data in the healthcare field are generalized to other fields which decrease the accuracy of the study. Researchers can widen their scope of research to include other industries. This would open up new areas to be tested, as well as it will highlight the industries that are interested in big data more than others.

Big data is an upcoming topic that can be tapped on from various perspectives. As such, researchers can still examine the acceptance of big data in functional firms, yet they launch a comparative study between different industries, which would give an increased load of data to be analyzed.

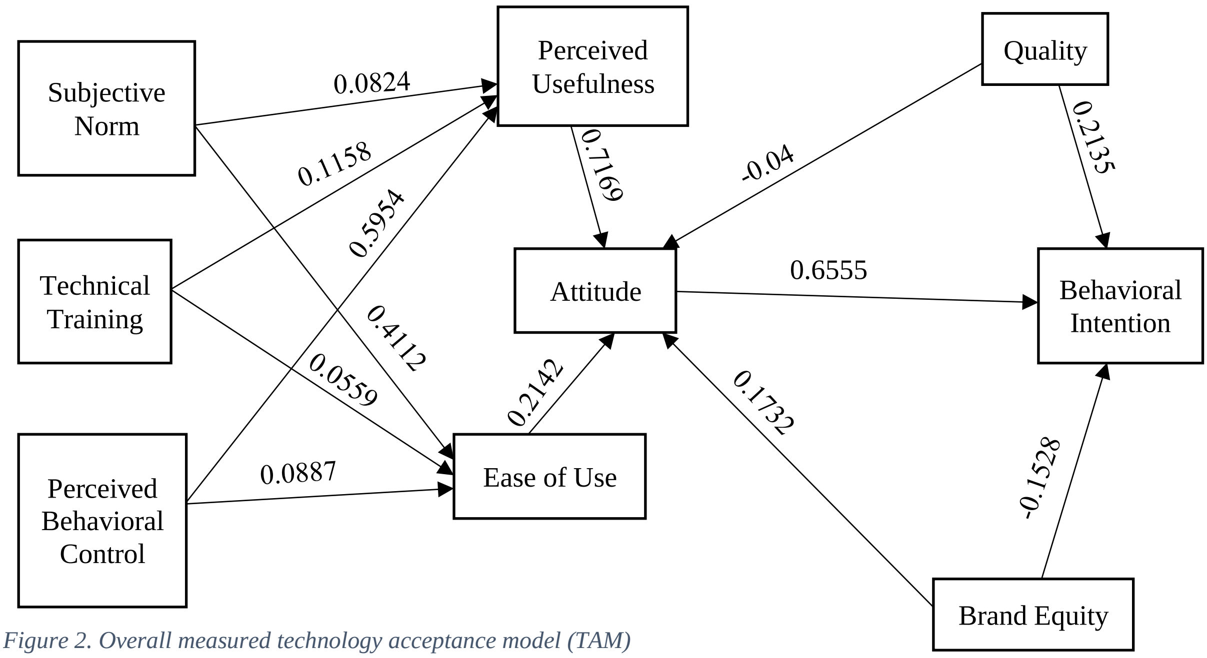

Figure 2. Overall measured technology acceptance model (TAM)

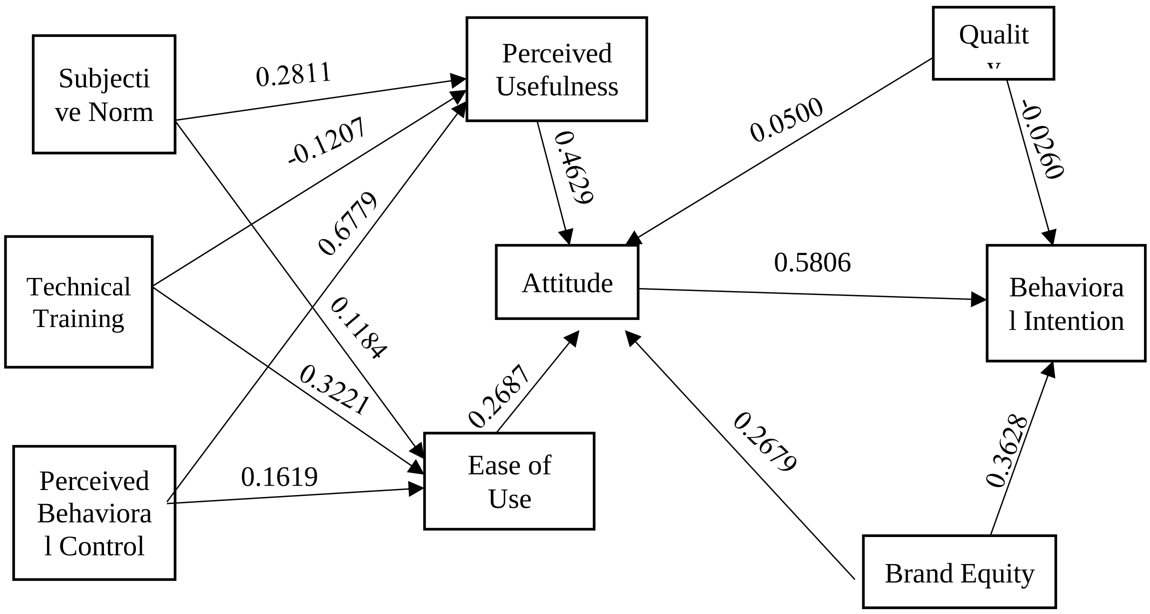

Figure 3. TAM model with path coefficients (India)

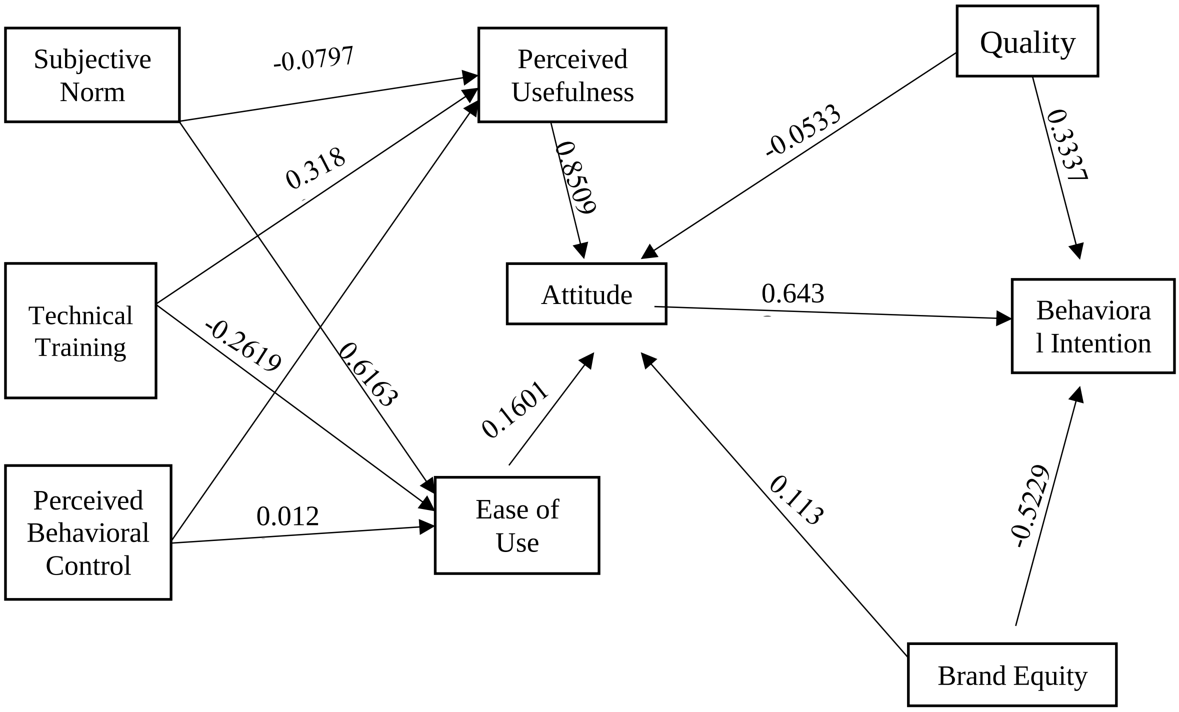

Figure 4. TAM model with path coefficients (USA)

	Path Coefficients (overall)	t-Values (overall)
Attitude -> behavioral intentions	0.6555	8.263
Ease of Use -> Attitude	0.2142	3.578
Per Usefulness -> Attitude	0.7169	8.180
Perc Beh Control -> Ease of Use	0.0887	0.674
Perc Beh Control -> Per Usefulness	0.5954	5.542
Techn Training -> Ease of Use	0.0559	0.380
Techn Training -> Per Usefulness	0.1158	1.005
brand equity -> Attitude	0.1732	1.325
brand equity -> behavioral intentions	-0.1528	1.028
quality -> Attitude	-0.0400	0.397
quality -> behavioral intentions	0.2135	1.986
subjective norm -> Ease of Use	0.4112	3.051
subjective norm -> Per Usefulness	0.0824	0.582

Table 4. Overall path coefficients and t-values of the measured factors

	Path Coefficients (United States)	**t-Values (United States)**
Attitude -> behavioral intentions	0.6433	3.6460
Ease of Use -> Attitude	0.1601	1.3521
Per Usefulness -> Attitude	0.8509	6.5503
Perc Beh Control -> Ease of Use	0.0128	0.0658
Perc Beh Control -> Per Usefulness	0.5486	2.5500
Techn Training -> Ease of Use	-0.2619	0.9647
Techn Training -> Per Usefulness	0.3189	1.5549
brand equity -> Attitude	0.1135	0.7012
brand equity -> behavioral intentions	-0.5229	1.6957
quality -> Attitude	-0.0533	0.3058
quality -> behavioral intentions	0.3337	1.3109
subjective norm -> Ease of Use	0.6163	2.9697
subjective norm -> Per Usefulness	-0.0797	0.3831

Table 5. Path coefficients and t-values of measured factors in the United States

	Path Coefficients (India)	t-Values (India)
Attitude -> behavioral intentions	0.5806	4.2354
Ease of Use -> Attitude	0.2687	2.6971
Per Usefulness -> Attitude	0.4629	2.8918
Perc Beh Control -> Ease of Use	0.1619	0.7186
Perc Beh Control -> Per Usefulness	0.6779	6.2263
Techn Training -> Ease of Use	0.3221	1.4502
Techn Training -> Per Usefulness	-0.1207	0.7641
brand equity -> Attitude	0.2679	1.2782
brand equity -> behavioral intentions	0.3628	2.0677
quality -> Attitude	0.0500	0.3123
quality -> behavioral intentions	-0.0260	0.1939
subjective norm -> Ease of Use	0.1184	0.7919
subjective norm -> Per Usefulness	0.2811	2.0544

Table 6. Path coefficients and t-values of measured factors in India

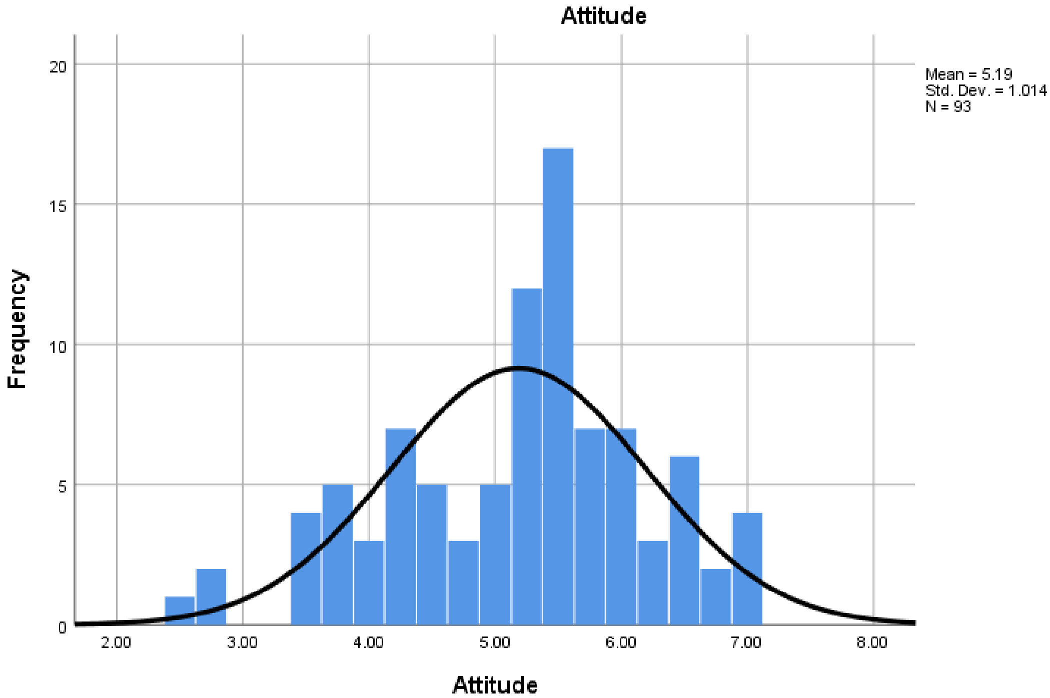

Figure 5. Histogram and Normality Check for Attitude

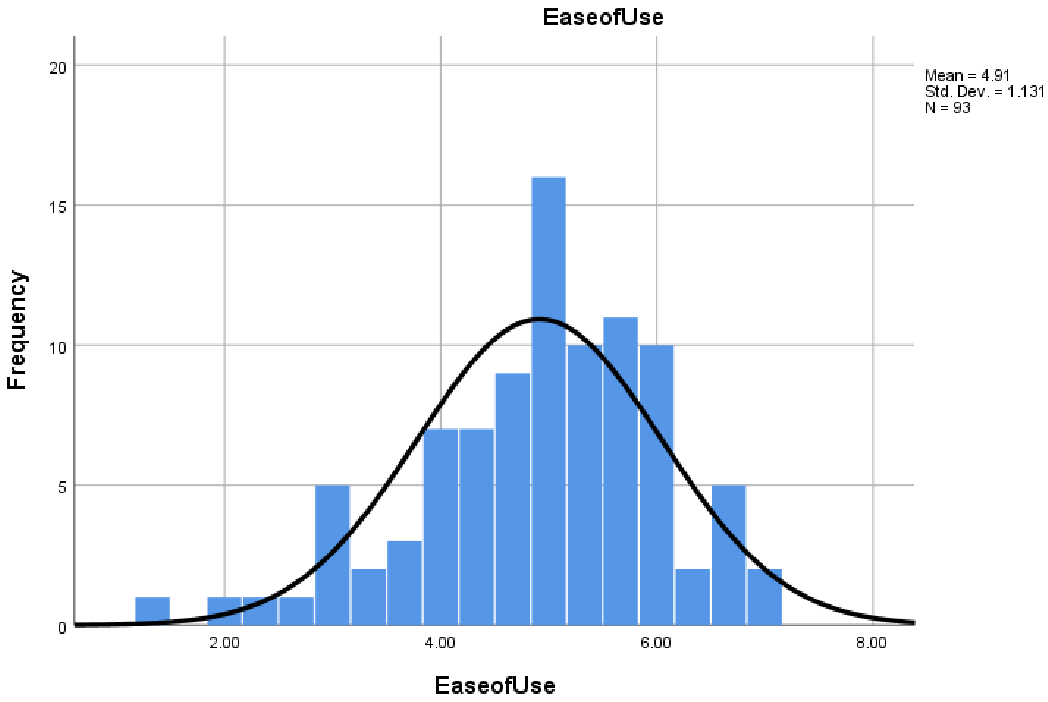

Figure 6. Histogram and Normality Check for Ease of Use

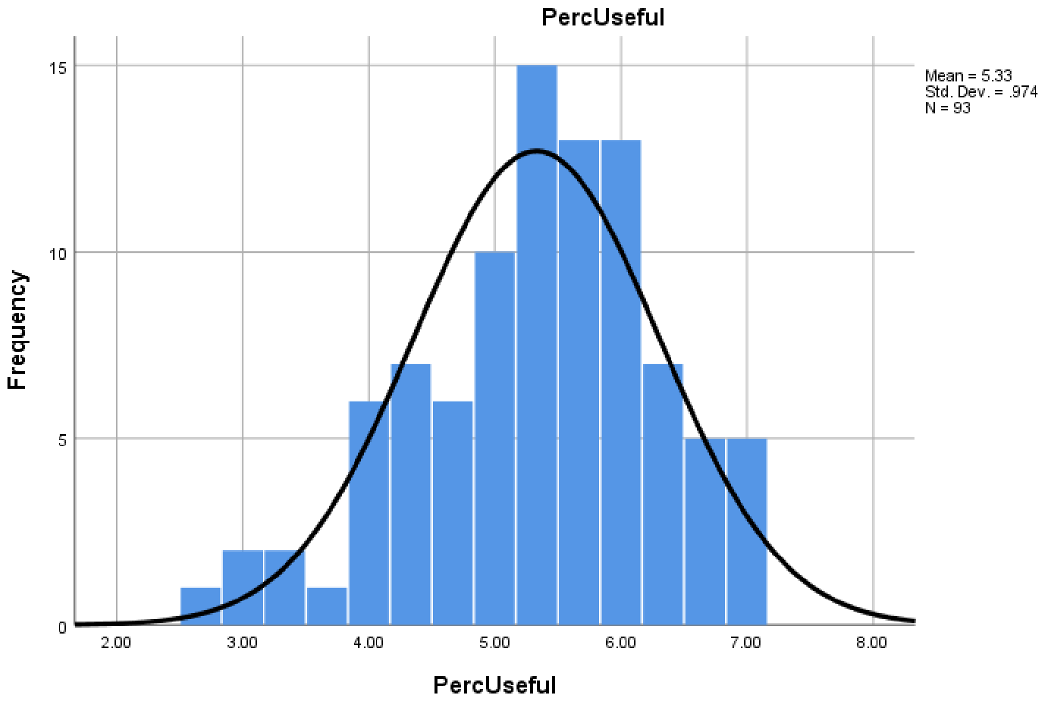

Figure 7. Histogram and Normality Check for Perceived Usefulness

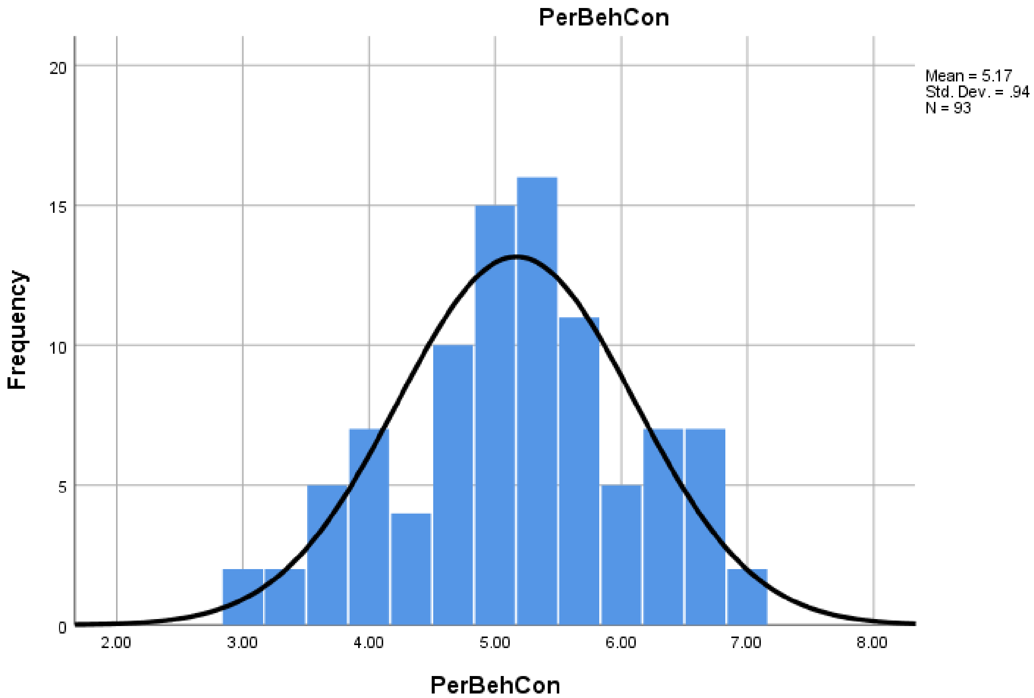

Figure 8. Histogram and Normality Check for Perceived Behavioral Control

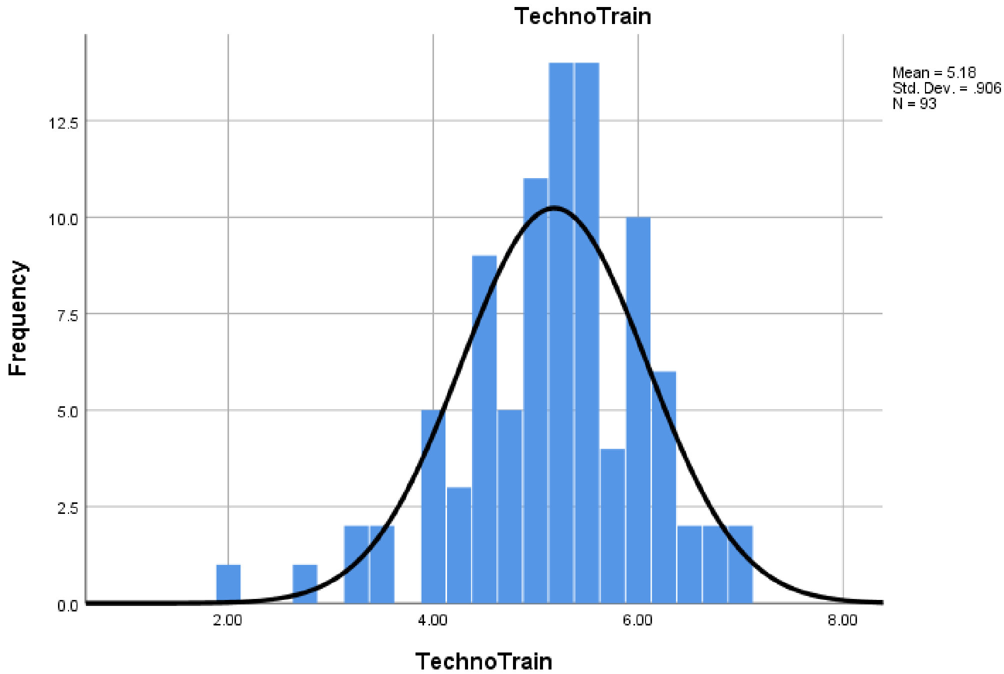

Figure 9. Histogram and Normality Check for Technology Training

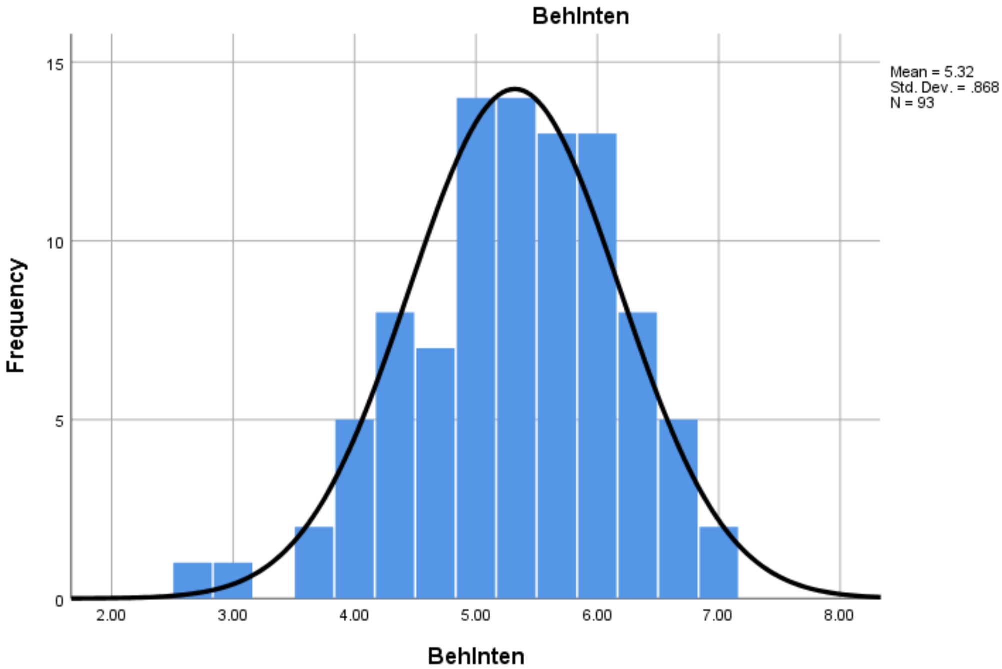

Figure 2. Histogram and normality check for behavioral intention

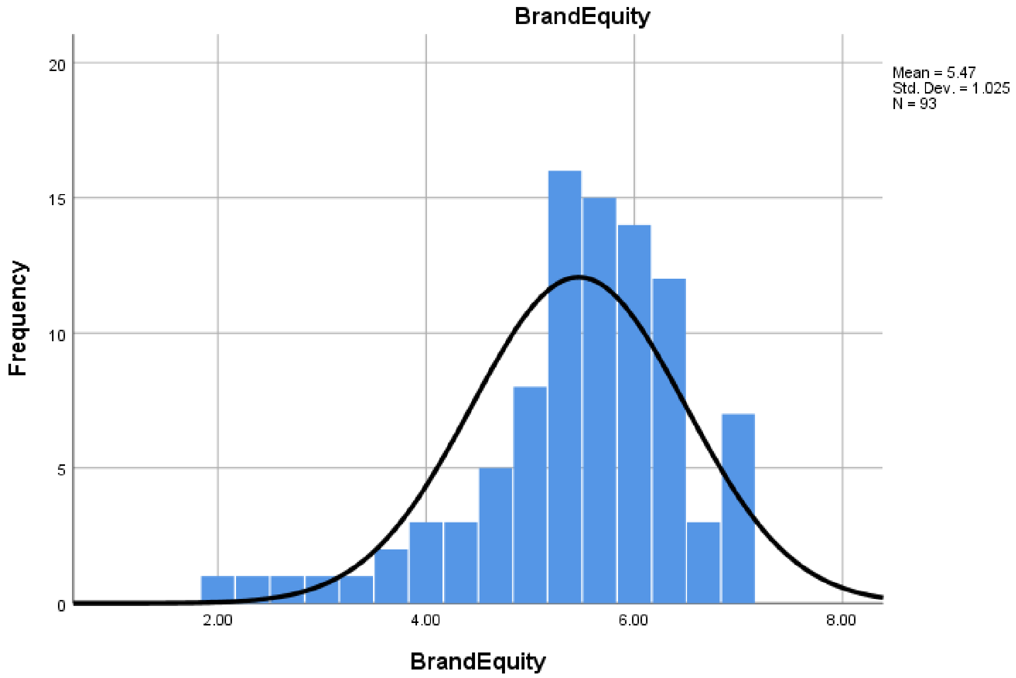

Figure 3. Histogram and normality check for brand equity

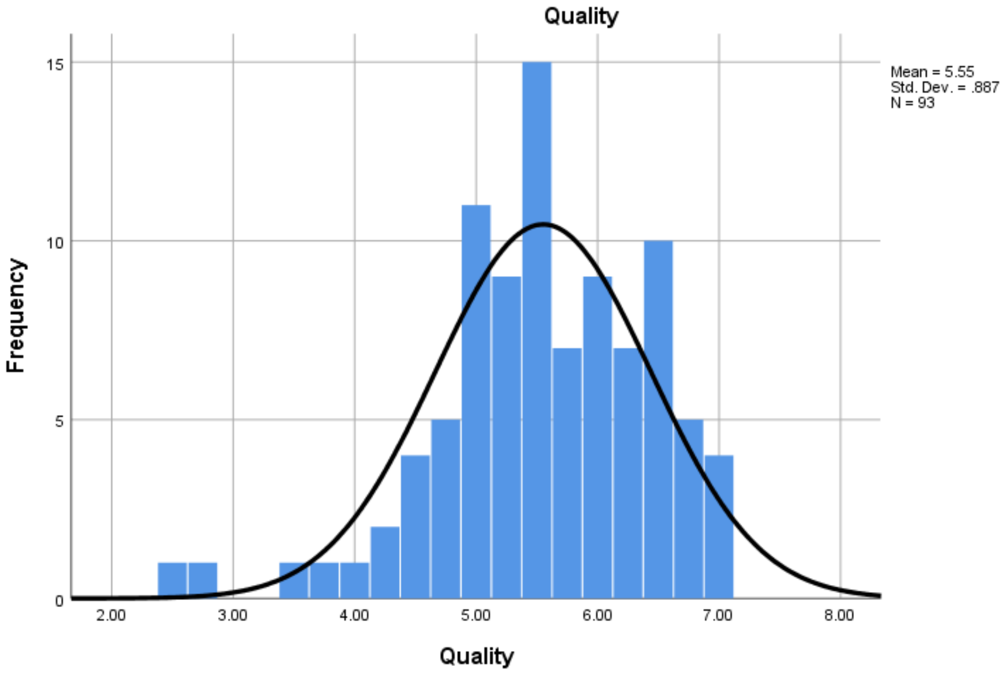

Figure 4. Histogram and normality check for quality

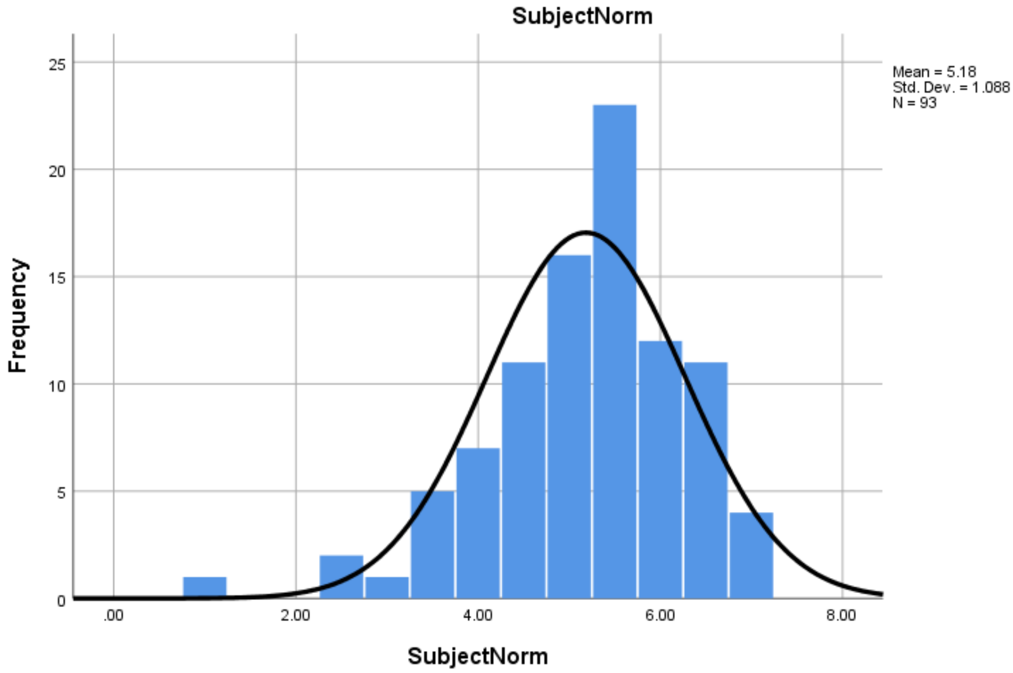

Figure 5. Histogram and normality check of subjective norm

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