POLITECNICO DI MILANO

Ingegneria Industriale e dell'Informazione

Master of Science in Management Engineering

SOCIAL NETWORKING SITES AND ADOLESCENT PSYCHIATRIC PATIENTS: AN EXPLANATORY MODEL OF THE USE

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Academic Year 2015-2016

Acknowledgements

This thesis work consumed huge amount of work, research and dedication. Still, implementation would not have been possible if we did not have the support of many individuals and organizations. Therefore, we would like to extend our sincerest gratitude to all of them.

First of all, we are thankful to Uludag University, School of Medicine, Department of Child and Adolescent Psychiatry, Bursa-Turkey for their cooperation and collaboration during the thesis work. We would like to especially mention **Halit Necmi Uçar**, **Ömer Kocael**, and **Şafak Eray** who devoted their time and knowledge to the implementation of this thesis. We would also like to express our sincere thanks towards volunteer personnel working at the clinic.

Furthermore, we are grateful to our supervisor and the researchers who helped us in many different ways.

Nevertheless, we express our gratitude toward our families and colleagues for their kind cooperation and encouragement which help us in completion of this thesis.

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Abstract

Fascinating developments in big data technologies and unprecedented diffusion of social networking sites (SNSs) not only generate unseen opportunities, but also pose an existential threat if not adapted for organizations from all sectors including healthcare. This study focuses particularly on the use of SNSs by adolescent psychiatric patients and the potential use of this SNS generated data to help medical practitioners diagnose and treat patients' mental health. Our objective is to understand and measure the conditions creating symptom-sharing on SNSs and the frequency of these conditions manifesting in symptom-sharing. Based on theory and previous research we conceptualized an explanatory model with causal relations between symptom shares on SNSs and perceived value and psychological safety. An empirical test of the model was conducted with a survey applied to 224 adolescents admitted to a psychiatry clinic in Turkey. The findings supported the model and suggested that adolescents would share symptoms on SNSs only if they attribute value to the SNSs that they use and if they feel psychologically safe in the SNSs. Moreover, the perceived psychological safety by adolescents positively moderates the influence of perceived value of SNSs on the amount of symptom share of adolescent on SNSs. We found that 72% of adolescents in our sample shared their symptoms on SNSs. Hence, there is an attractive opportunity for the development of a software program for detecting symptoms to support psychiatrists in their diagnoses.

1-Introduction

In the last decade, the world experienced digitalization of all aspects of people's life at an incredible pace and much faster development and diffusion of information technologies (IT). The recent trends in digitalization and IT have led to a concept called big data, which is embraced by many sectors from banking to retail. However, the healthcare sector lagged behind other sectors in terms of adopting big data, although it is estimated that big data can generate $300 billion yearly in healthcare sector (Groves et al. 2013; Roski et al. 2014).

Big data is generally defined as data sets that are too large to handle them using traditional data storage and processing techniques (Luna et al. 2014; Ebenezer and Durga 2015). Although there is not a consensus definition, most scholars agree on three defining features of big data that the company Gartner, Inc. originally proposed. These three components include high volumes of data, high variety in data, and high velocity of data creation. Some also consider a fourth feature, veracity, when defining big data. Veracity refers to confidence level of each data in the data set. Additionally, big data is used as an umbrella term meant to encompass the production of data, its consequences, and the work done to process the data. Due to the ambiguities in the term big data, and its use a buzz word, it remains difficult to define the scope and specific details of big data.

There are plenty of data in healthcare industry, which create promising opportunities for big data technologies. The data can be explained in three categories according to the sources. First category is the healthcare systems data, which covers administrative data of healthcare organizations, laboratory data, patient diagnosis etc. Recently electronic health record (EHR) systems are developed to store, handle, exchange and analyze this data. The second category is the data generated by genomics. With decreasing costs and faster methods of sequencing genomes, data generated by this field is exploding. The final category can be named as self-generated data because it is the data generated by the final consumers of healthcare services. Some examples of this category are online searches and internet activities, data generated in social media platforms, data generated in blogs and forums, data generated by mobile apps, data from wearable devices, and data from the internet of things (sensors). Big data technologies for creating value from this data can also be categorized into three: Data storage, processing, and mining technologies. Thank to the development of cloud technologies, data storage and processing become widely available at a much more affordable price and faster speed. Everyday, new algorithms are being developed by academicians and professionals for data mining purposes (Hansen et al. 2014).

Big data can create value in healthcare in several ways, including supporting the trending approach of 4P-medicine, which stands for predictive, personalized, preventive, and participatory medicine. Using big data, one can use predictive analysis to intervene before any illness. EHR data and genomics data can be used to design personalized medicine. Using accurate predictions and personal information, preventive medicine can be used to keep individuals healthy. With communication platforms and data shared between patients and caregivers, patients can be active participants in making decisions about their health and lifestyle. This 4P approach is exactly that- an integral discipline that identifies one's health and lifestyle as intertwined (Holzinger et al. 2015).

For advantages of big data to be capture in healthcare, there are certain challenges to be addressed. Privacy and security concerns related to patients' data and big data supporting policy and regulations are the most important challenges. Also, incentivizing doctors for embracing big data and training data scientists who are also healthcare domain experts can be mentioned to be addressed for big data developments in health care (Roski et al. 2014; Bates et al. 2014; Kuziemsky et al. 2014).

One of the data sources for healthcare is social networking sites (SNSs), which are relatively new but changing people's lives and so all sectors including healthcare. A milestone for the success of these platforms was MySpace with its enormous user base and company value of $500 million in 2005 (Alexa 2016). Later on, different SNSs became popular for each region in the world and this is still valid for China and Russia. In 2004, the Facebook was founded by Mark Zuckerberg and focused primarily on university students network site. In 2005, Facebook became social networking site open access to everyone. Facebook have been enormously popular in most part of the world and in 2016 reached 1.65 billion monthly active users. It has been leading the SNSs in the world in terms of the number of countries used the most and the number of users since 2014 (Facebook 2016). SNSs' user profile is mostly young people who are aged between 18-29 (Lenhart et al. 2010).

There are numerous possible uses of SNSs in healthcare to create value for people and companies. Delivering healthcare services via SNSs is one option which can be valuable especially in developing countries where many patients never see a doctor or visit a clinic even if they vitally need it. Currently, many healthcare organizations provide healthcare information via SNSs with the purpose of public training in health related topics. Almost 95% of hospitals in the US have Facebook pages (Fernandez-Luque and Bau 2015). SNSs also give people a chance to exchange health related information so that they benefit each other experiences which might be a kind of information that is not available in official health information sources (Blumenthal 2011).

Extracting valuable information from the huge amount of data generated by SNSs is another possible use of SNSs for healthcare. While public surveillance can be done with SNSs data at a much lower cost and faster, individual data of patients can also be used for supporting health related decisions after receiving consents of patients. One important and valuable use of individuals' data on SNSs is that diagnosis of mental health problems can be supported with SNSs' data (Kuziemsky et al. 2014).

This study focuses particularly on the use of SNSs by adolescent psychiatric patients and the potential use of this SNS generated data to help medical practitioners diagnose and treat patients' mental health. American Academy of Child and Adolescent Psychiatry (2015) states that "The child and adolescent psychiatrist is a physician who specializes in the diagnosis and the treatment of disorders of thinking, feeling and/or behavior affecting children, adolescents, and their families". As the developments in this relatively new field of psychiatry, scholars and physicians understand its importance better as mental problems in childhood, if not treated, might permanently affect one's whole life. Considering adolescents' high use rate of SNSs and their high disclosure of emotions, we chose to SNSs and adolescent psychiatry.

In the current state of literature, there are studies related to adolescents' behaviors and habits on SNSs. Their reasons of using SNSs, their level of emotion disclosure and its drivers were studied in the past. Some scholars focused on SNSs addiction and its effects on child and adolescent psychology. In terms of using the data generated by adolescent on SNSs, some scholars studied public surveillance applications and some others studied possibility of detecting psychiatric symptoms from individuals' SNSs data.

As a result of literature review and observing literature gaps, we understood that detecting psychiatric symptoms of an adolescent using her or his data on social networking sites is possible with available technology. Although there are many academic studies and trial applications of this idea, currently there is not a practical standard use of the idea in healthcare systems. Moreover, the results of such pioneer works are neither conclusive nor complete in terms of validity or universal applicability. Therefore, there is not a consensus about whether detecting psychiatric symptoms using SNSs data is possible all around the world in a reliable manner.

The objective of this study is to investigate the possibility of detecting child psychiatry symptoms from SNSs data. Considering the existence of advanced social network mining techniques, we assume that the symptoms can be detected as long as adolescents share their symptoms. In other words, current state of technology is capable of analyzing social media content of a person and detecting psychiatry symptoms if shared. This reduces our investigation to whether adolescents share their symptoms on SNSs. With this purpose, a survey has been conducted for adolescents admitted to a child and adolescent psychiatry outpatient clinic in Turkey. The main goal of the survey is to understand under which conditions and how frequent patients share their symptoms on their SNSs profiles. The survey was prepared and conducted with the collaboration of Uludag University, School of Medicine, Department of Child and Adolescent Psychiatry, Bursa-Turkey. We conceptualized a novel explanatory model with causal relations between symptom shares on SNSs and perceived value and psychological safety. An empirical test of the model was conducted with a survey applied to 224 adolescents admitted to a psychiatry clinic in Turkey.

2-Literature Review

2.1-Big Data in Healthcare

2.1.1-General Introduction to Exponential Data Generation

In the world today almost every aspect of our daily lives is digitalized. The boom of internet-based technologies has led to an enormous amount of data creation for all. In the last two years, people have generated a greater amount of data than in any other time in the history of humanity (Luna et al. 2014). According to IBM Corporation, 10 billion mobile devices will be used by 2020, and over one billion Google searches occur every day. Trillions of sensors are recording and sending data, and as much as 30 petabytes of data are generated by Facebook users. As one can understand from all of these numbers, people today are creating a huge amount of data (IBM Corporation 2016).

All of this data is generated by the vast majority of people in the world. Based on the ‘Measuring the Information Society Report’ from 2015, 7.1 billion mobile devices are used globally with the prices for such devices continuing to fall. Almost half of the global population, 46.4% of people, used the internet as of 2015, with access and demand continuing to increase. In terms of mobile internet, the numbers are significantly higher. Worldwide statistics show that there are 96.8 mobile phone subscriptions per 100 people, and 95.3% of the population was covered by a 2G mobile cellular network. (Measuring the Information Society Report 2015). This buildup of data leads to new tech developments in terms of data storage, processing, and analysis.

These developments are all forcing businesses across different sectors to adapt to changes in established organizations and traditional business sectors. Data generation and new technologies are changing so quickly that scholars and business professionals call it 'disruptive' change, as opposed to incremental innovations and developments that businesses can learn and integrate over time. These new disruptive technologies force companies to commit their time, financial resources, and human resources or potentially face significant business loses. Across market sectors, businesses need to remain constantly informed about ever-improving technological advantages.

Like all other sectors, healthcare is prone to the growing demands in data and technology. For example, Electronic Health Record (EHR) systems generate much data as the system holds information concerning each individual patient. There are many different sources in healthcare data as well, with EHR systems representing only one of many critical types of medical and healthcare data sources. All of these sources are estimated to produce 25,000 petabytes of healthcare data by 2020 (Panahiazar et al. 2014; Roski et al. 2014). Looking at Kaiser Permanente, which has 9.6 million members in multiple American states, the group manages 44 petabytes of data. This data is 4,400 times bigger than that of the Library of Congress (Roski et al. 2014). As one can see from this example, the healthcare sector generates, stores, and processes data to meet the needs of millions and millions of health patients.

Players like Kaiser Permanente try to take advantage of this massive volume of data to create a competitive edge for themselves. Continued data creation affects all the players in the sector, by introducing companies with opportunities to build competitive advantages or face threat to the longevity of their businesses. The threat that big data poses for businesses is one of the reasons why big data is such a critical element. People need to adapt or be excluded as people rely more and more on syncing businesses, health, and everyday lives to technology.

2.1.2-Definition Big Data

The trends mentioned above, i.e. exponentially growing data generation, new data technologies, and disruptive changes in all business sectors, lead to a concept called ‘big data’.

This is a rapidly changing new field with a constantly evolving definition. Generally, big data is defined as data sets that are so large that it becomes impossible to handle them using traditional data storage and processing techniques (Luna et al. 2014; Ebenezer and Durga 2015). Although there is not a consensus definition, most scholars agree on three defining features of big data that the company Gartner, Inc. originally proposed. These three components include high volumes of data, high variety in data, and high velocity of data creation. Some also consider a fourth variable, veracity, when defining big data. Additionally, big data is used as an umbrella term meant to encompass the production of data, its consequences, and the work done to process the data. Due to the ambiguities in the term big data, and its use a buzz word, it remains difficult to define the scope and specific details of big data.

2.1.2.1-Volume

Volume refers to the size of data generated and stored (Luna et al. 2014). It is exponentially increasing due to decreasing costs for storage and increasing devices and people generating data. This huge raw data contains valuable information and knowledge but it requires advanced analytical skills to extract meaningful information and knowledge. In healthcare, the amount of data is quite large, as mentioned above with

Kaiser Permanente. Forty-four petabytes of EHR data or 25,000 petabytes of data by 2020 are enormous figures. These numbers are growing to parallel a large percentage of society associated with high quality medical services.

2.1.2.2-Variety

Variety refers to data that contains different data types and formats, which can be unstructured, semi-structured or structured data. For example, text, picture, tables, videos, etc., represent some of the many different types of data commonly used. Data related to healthcare has a very high variety. It varies from lab results and doctor prescriptions to giant files containing the entire genome of an individual. Additionally, users can also generate healthcare data through social media activities and self-quantifying devices, which adds much data to the already existing traditional sources.

2.1.2.3-Velocity

Velocity refers to high speed data generation. Every minute more and more data is generated from different devices. High velocity of big data allows companies to gain more information faster and make better business decisions. In order to do this, big data needs to be processed at the same speed as data collection. Healthcare services quickly adopted EHR systems as information banks for patients and staff; EHR also has a high velocity of data generation. Patients also generate data through online activities like social media, internet searches and browsing histories. Self-quantification activities like FitBit also store and process data to help users with their fitness needs. All of this data generated at very high speeds marks an opportunity to keep track of individual patients during treatment. Considering its use at a macro-level, it also creates an opportunity for fast and timely public health surveillance (Kuziemsky et al. 2014). The coming chapters will explain in-depth how these opportunities are presenting themselves through high speed data generation.

2.1.2.4-Veracity

As mentioned above, some scholars add veracity to the original group of terms used to define big data. When discussing veracity, it refers to the confidence level of each data. Because of high variety and volume, big data consists of data with both very high and very low confidence levels. The confidence level of the data specifically organizes reliable data, useless data, etc. When extracting information and knowledge from big data, confidence levels of information and data remain pertinent. In healthcare, this is especially critical because a lab result and self-measured data, for instance, do not have the same accuracy, which therefore affects its credibility.

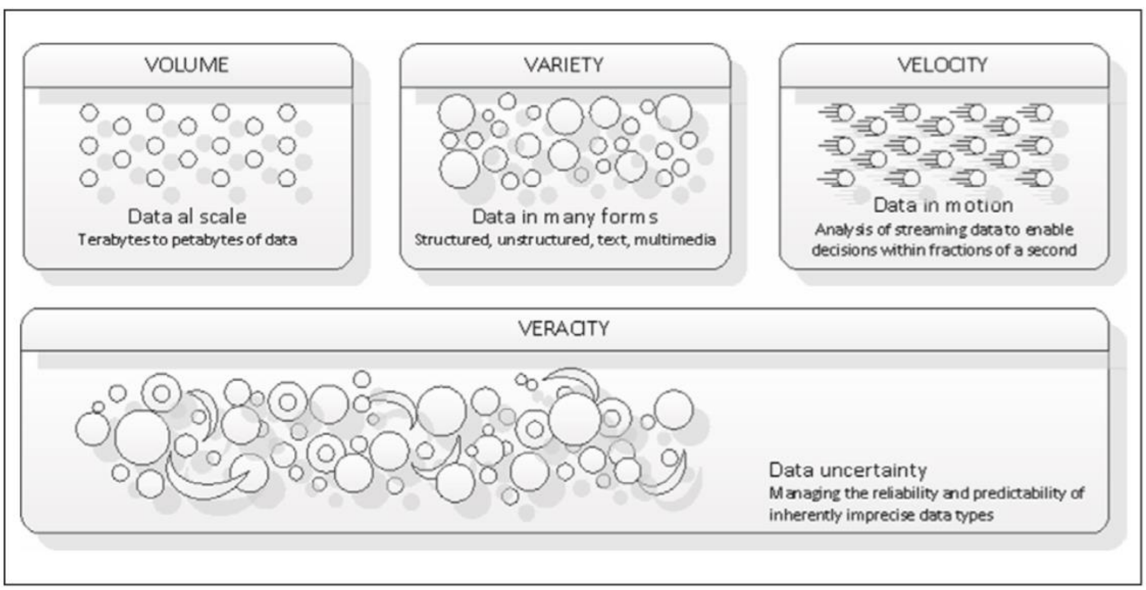

Figure 1: The Three Features of Big Data (Luna et al. 2014)

2.1.3-Data Sources in Healthcare

Healthcare data can be categorized according to its sources: healthcare systems data, genomics data, and self-generated data. All of these categories create large quantities of data by themselves, valuable data which can help healthcare organizations work more effectively and efficiently. This report categorized data sources considering the fundamental differences between the data and its processing needs, as one can see below.

2.1.3.1-Healthcare Systems Data

This category includes all the data that is generated during the regular course of healthcare systems. This group varies widely, depending on the technological integrations of each healthcare system, and specific health needs. In this category one can consider the following types of data: administrative data, laboratory data, patient diagnosis, prescriptions, doctors and nurses' notes, data from pharmacies, insurance claims, academic papers, and EHR.

Administrative Data- Any healthcare facility has administrative software to manage its operations. This software often creates and stores valuable data, using this data for administrative and managerial purposes. Examples of this type of data include patient registries and discharge data, human resource data, supply chain data (e.g. Enterprise Resource Planning Software data).

Laboratory Data- In healthcare systems, laboratories hold an important role in diagnosis, treatment, and outcome measurement phases. Laboratories produce important data for healthcare and this data is usually stored in the laboratories' data management systems. Examples of this data include lab test results, pathology results, imaging tests like MRIs or magnetic resonance imaging tests, x-rays, ultrasounds, and ECGs or electrocardiograms. All of these results also contain information useful for quality assurance purposes, known as metadata; this includes name, data, time, container type, preservative, etc.

Patient Diagnosis, Prescriptions, and Doctors and Nurses Notes- Traditionally, this data was written on paper notes by healthcare professionals. Although this data is valuable, most health professionals used personal storing methods. Recently, some organizations in healthcare have started using software to store this data, and providing necessary technology to integrate doctors, nurses, and other professionals into the system. Storing this data is also important for scientific research and for healthcare planning.

Data from Pharmacies- The data from pharmacies includes prescription and non-prescription medicine purchases, inventory management, and supply chain management.

Insurance Claims-Insurance claims contain all data concerning services that a patient has received from a healthcare provider. The claims themselves represent formal client requests to receive compensation for all of the costs associated with their medical needs. These claims are well-documented and well-structured with comprehensive medical data. It gives an opportunity to have much the data related to one person's health record.

Academic Papers- In the healthcare sector, most of the know-how and scientific knowledge is stored in the form of academic papers. Therefore, the data stored in this form is incredibly valuable. Easy, fast access to data with the option of systematic searches or classifications remains very important for further development in healthcare. IBM Watson is a software which tries to address this issue by using natural language processing and machine learning. Ultimately, professionals hope to use software to gain insight and wisdom from unstructured data like text files (IBM Corporation 2016).

EHR, Electronic Health Record- All of the administrative data is generated and stored in the healthcare systems, and traditionally each data is stored where it is created. For example, administrative data for each organization's administrative data is traditionally stored in the organization's data management system where the data was originally created. Therefore, data integration is hindered due to limited communication and limited data exchange between different healthcare facilities. Data integration can create further value for all stakeholders because of the wide scope of information related to each patient. Thanks to advances in recent IT technologies, collecting, systemizing, and exchanging the data among parties now exists in a much easier and more obtainable manner; this represents the core of EHR systems and their purpose. As said by Hayrinen (2008), "EHR means a repository of patient data in digital form, stored and exchanged securely, and accessible by multiple authorized users." In these records, all the data related to a specific patient can be found in a chronological manner including the source of each data. The data related to a problem of a specific patient can also be extracted in way that contains assessments of the problem, aims, planning and delivery of the intervention, and outcomes.

The components of EHR are not limited to: past medical history with familial health included, allergies, active problems, test results, medication, symptoms, complaints, diagnosis, referrals, life style, admission nursing notes, immunizations, laboratory results, clinical findings, clinical orders, and other condition-specific information (Hayrinen 2008). In this system, some of the data is stored in a structured form which can be easily extracted, analyzed, and used. However, this data might also include semi-structured or unstructured information. For example, lab results can be in different formats like image files or time series files. Similarly, medical notes can be in a text format or in an unstructured form. Due to these challenging factors, advanced big data analytics are necessary to analyze the data.

2.1.3.2-Genomics Data

Genomics is a scientific field that deals with structure, function, evolution, and mapping of genomes. Because a human genome contains huge amount of information, sequencing a human genome generates large data files. With decreasing costs and faster methods of sequencing genomes, data generated by this field is exploding. Other biological and molecular fields should also be mentioned considering their data generation pace. Microbiomics, proteomics, and metabolomics are some of these fields, which are called 'omics' in general. Thanks to these fields, mechanisms of diseases can be examined at individual levels. This has created a huge potential in terms of personalized medicine. Although these fields are developing quickly, they are still not integrated in the majority of standard healthcare systems. Only specific organizations started to use genome data to detect patients at risk for preventive medicines or for customizing the patients' medical treatments. Currently, these types of data are not stored in EHR systems mainly because of the cost of generating the data for each individual, and the incredible size of the data. However, there are initiatives to use omics data and EHR data together to create value by preventive and personalized medicine (Belle et al. 2014).

2.1.3.3-Self-Generated Data

In this category, data is generated by the final consumers of healthcare services. Although traditionally healthcare consumers were generating only some limited data, nowadays the size of the data that they generate is exponentially increasing. Some examples of these types of data will be considered, including online searches and internet activities, data generated in social media platforms, data generated in blogs and forums, data generated by mobile apps, data from wearable devices, and data from the internet of things (sensors).

Online Searches and Internet Activities-

People are using the internet for their health more and more consistently, which creates a lot of potentially valuable data. One way of generating this type of data can be as simple as using search-engines for health related topics. According to a report requested by the European Commission called 'European Citizens' Digital Health Literacy Report' (2014), 56% of people in Europe searched health related information online. More than half of the population searched for general information and disease specific information, representing 55% and 54% respectively. In terms of treatment specific information, 23% percent of searches met this criterion. Finally, ten percent of people searched about second opinions after visiting a doctor.

Concerning the types of websites used, between 82-87% of people used search engines, and almost half used websites like forums and blogs. Official websites represented roughly one third of the searches, and a quarter of the searches sourced magazines and newspaper sources. Finally, around 20% of people used social media websites and 15% of people used mobile apps.

Table 1: People's Use of Different Type of Websites

Search Engines	82-87%
Dedicated Websites, Forums & Blogs	47-48%
Official Websites	33-38%
Magazines and Newspapers	20-26%
Social Media Website	16-23%
Mobile Apps	13-17%

An example of the usefulness of this data is shown by Ekström and colleagues (2015). They developed a model for "forecasting emergency department visits using internet data".

Data Generated in Social Media Platforms-

With the rise of social media websites like Facebook, Twitter, and YouTube, their use in healthcare is also increasing. The activities of millions of people using these platforms create a huge amount of data that maintains much potential for healthcare companies. Looking at Twitter alone, Hansen and colleagues (2014) report that 16.6% of the tweets are related to health, representing great potential. Afyouni and colleagues (2015) also conducted a Twitter sentiment and network analysis about digital health. They showed that the public maintained a positive opinion about digital health, which is promising to the field. Social platforms remain important communication channels of today's world, and for healthcare they can be used by all stakeholders to better communication.

People are interacting and sharing data through social media sites, connecting patients, professionals, and hospitals connecting with each other. Patients with similar health problems are also contacting one another, supporting and sharing experiences through social media or websites such as patientslikeme.com (Fernandez-Luque and Bau 2015). Additionally, hospitals remain active on social media and other online platforms to reach their customers. Almost 95% of hospitals in the US have Facebook pages, like 67% of European hospitals as of 2011 (Fernandez-Luque and Bau 2015).

The importance of social platforms is beyond communication. Individual or personal data can be used to support patient diagnoses and scientific progress. For example, Kuziemsky and colleagues (2014) state that automated analysis of social network usage data can be used to support diagnoses of mental health problems such as depression and schizophrenia.

Data Generated in Blogs and Forums-

There are many health related blog and forums, which people use to share personal health data and advice among patients, consumers, and medical practitioners. The experiences that people share about healthcare in blogs and forums can be very unique by nature, because it can contain candid personal information and case details that professionals would otherwise lack.

Data Generated by Mobile Apps-

With the proliferation of smart phones and mobile applications, people are using applications for virtually every aspect of their lives. There are numerous applications related to healthcare, representing a huge data source for healthcare. Fernandez-Luque and Bau (2015) report that there are more 1,100 apps (iOS and Android) to manage diabetes alone. People also take advantage of smart phones by using the phone-generated data from their sensors, including location and acceleration data. This data might be useful for patients and health professionals, as the devices count steps per day and analyzes the effects of the results for one's health. The same information proves relevant when people use apps to control their food consumption and ensure it meets dietary needs. This process is also considered within the 'Quantified Self' movement, which uses technology to collect comprehensive data which considers many different factors, not limited to consumption, mood, physical and environmental circumstances. Applications and wearable devices take advantage of the quantified self movement, and use this systemic technological integration to generate valuable data.

Data from Wearable Devices-

Data from wearable devices can be obtained individually through vehicles as common as computers, smartphones, wearable devices like Fitbit bracelets, and activity trackers to collect personal metrics about daily life and health. As the movement gains momentum, more and more people are generating data about their health, which can be quite useful for healthcare. Thanks to this data, physicians can have detailed continuous patient data to track the outcomes of different treatments.

Data from the Internet of Things (sensors)-

As the popularity of the internet of things and smart environments increase, the data from these sources continues to grow exponentially. This data can be highly valuable for healthcare because it can allow people's individual metrics to be tracked and compared, which can catch patterns in a person's health or provide other information that can benefit the person's medical status. For example, one of the many uses of this data focuses on tracking elderly people's movements from home. This is both affordable and practical, because a healthcare worker can be dispatched automatically if a lack of movement or abnormal moment trends occur. This can dramatically decrease the cost of care for the elderly.

2.1.4-Big Data Technologies

2.1.4.1-Data Storage

Relational database management systems (RDBMS) can be considered the traditional solution for data storage. These databases can store files in different formats, from text files to image files. The data is stored in the form of tables, and relationships are defined between tables that link the data together. These types of databases require ETL (extraction, transformation, and loading) tools to store any data. The output uses ETL tools to generate structured data which can be obtained and stored, but structuring each piece of data can be time-consuming, consequently limiting the data loading speed of the database. This is an obstacle for big data considering its high velocity feature. Moreover, RDBMS systems are memory intensive which means that they require a large storage capacity. As the size of stored data increases, the cost of storage systems also increases dramatically. Additionally, readings from the database also require a specific query language (such as SQL), and the readings are processor-intensive processes. It is not uncommon that these readings require considerable amounts of time depending on the complexity of the query. Overall RDBMSs lack fault tolerance, linear scalability, and more importantly handling they lack unstructured data considering the needs of big data (Raja et al. 2015).

To overcome the mentioned limitations of this traditional solution, cloud storage and computing was developed. Cloud storage and computing is based on distributed storage and parallel processing techniques. Apache Hadoop is one of the open source frameworks for this technology. In this framework, there is one master node and a number of slave nodes. Each node consists of a storage and processing unit. While the master node stores the metadata of all the data stored in the system, the slave nodes store the real data and process them. Processed data, created by slave nodes, is then sent to the master node for data integration. This represents the final aspect of a typical data retrieval process.

In RDBMS, specially designed and expensive hardware is necessary for handling relatively large data, which represents a major drawback when considering this more traditional system. Cloud computing is compatible with commonly found storage and processor units, which are much cheaper. With the cloud system, data which require storage does not require a preprocessing or structuring operation before said storage. Data can be stored as is, and when the data requires a certain format the data can be parallel processed. This is a great advantage over RDBMS in terms of storage and retrieval of speed and capability. Increasing the storage capacity of these systems is much cheaper because of commodity hardware use. Therefore, the data can be copied more easily, and more copies allow a greater scale of fault tolerance that would be much more difficult if hardware were more expensive. Overall, this system is superior to RDBMS in terms of fault tolerance, linear scalability, and the handling of unstructured data.

2.1.4.2-Data Processing

For traditional RDBMSs, a centralized data processing unit is necessary. As the size of data storage systems increase and the need for faster processing increases, more powerful processing units are necessary. These high-tech super processors are quite expensive, and the systems are frequently called high performance computing (HPC) systems. One well-known example of this type of processing unit is Intel Xeon Phi, which can provide up to 1.2 teraflops of performance. According to top500.org, a credible website ranking high performance computers, the first supercomputer (Tianhe-2) on their list is equipped with Intel Xeon Phi (Merelli et al. 2014).

As a response to the high costs of processors, a new technology has been developed which uses graphics processing units (GPUs) as an accelerator device. GPUs are cost effective and able to provide high computing powers that are comparable to processors like the Intel Xeon Phi. For example, the AMD Radeon R9 295X2 graphics card can provide up to 11.5 Teraflops and costs around $1,500 US dollars. The second supercomputer on the list of top500.org, uses a GPU called NVIDIA K20x. GPUs' main advantage comes from their ability to use massive parallelism for simpler tasks. Therefore, their high performance is useful only when a problem to be computed is easily parallelizable.

Compared to the mentioned traditional computing solutions, cloud computing is considered as the most advanced and promising technology. As explained above, a typical data retrieval process is programmed in the MapReduce model in Apache Hadoop framework. MapReduce programming model uses parallelization for each query, which is mapped to a number of slave nodes in the system. The slave nodes process the query on the data stored in themselves. The final results of slave nodes are sent to master node and master nodes reduce them into one final result. This model does not require expensive processors. Thanks to its ability to linearly scale and handle unstructured data at reasonable costs, it can support big data with its high volume, high velocity and high variety. As all the companies and sectors demand big data technologies and the expansion of fast internet, it is possible to offer cloud storage and computing as a service. Google cloud services, Amazon S3 and Microsoft Azure are examples of such services (Ebenezer and Durga 2015). This possibility brings forth many opportunities to use big data for organizations with less competence and resources in IT.

2.1.4.3-Data Mining

In 2007, Rowley explained the data-information-knowledge-wisdom hierarchy. He claimed that any information system requires copious data storage, which is presented in the bottom tier of the pyramid. Using basic computing techniques, the information system generates information that is represented in the second tier of the pyramid. The previous two sections of this report addressed cloud-storage and cloud processing as essential solutions for information and data within the pyramid. Concerning the rest of the pyramid, knowledge creation and wisdom are critical components necessary to reap all of the benefits of big data. Advanced analytical methods are required to create knowledge and wisdom from data and information. Scholars also define this process as revealing hidden knowledge and wisdom from data. Scholars and professionals frequently refer to this process as data mining.

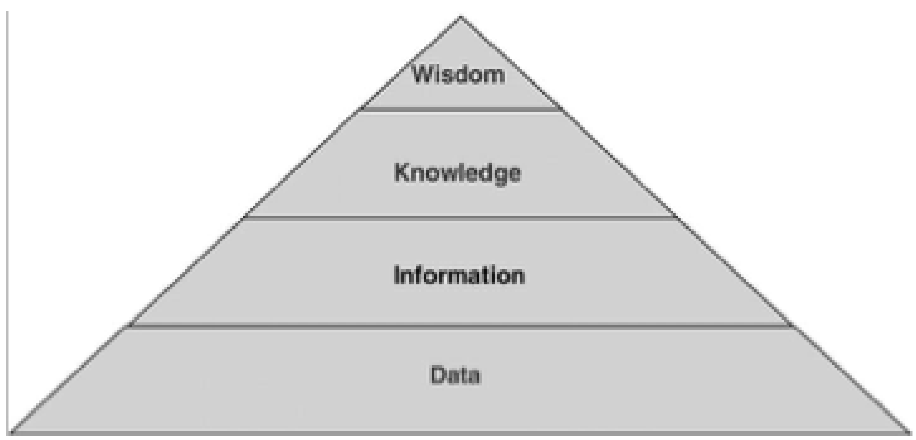

Figure 2: Data-Information-Knowledge-Wisdom Hierarchy Pyramid (Rowley 2007)

Data mining techniques and algorithms are developing rapidly. There are three main drivers behind this development: high demand for data mining by all sectors, wide availability of data, and cheaper computation costs. Every day, software developers create new algorithms or improving existing ones. This high growth makes it quite difficult to produce a complete current list of algorithms. At the same time, classifying algorithms proves difficult because the algorithms are modified and combined, which skews potential categories from distinguishing themselves. Therefore, this report highlights only the most widely used algorithms and techniques.

Data mining algorithms can be descriptive or predictive. Descriptive analysis tries to reveal the hidden patterns in data with purpose of better understanding the data. On the other hand, predictive analysis uses historical data to make predictions about the future. Some of the basic techniques are regression, time series analysis, classification, association rules, and clustering. Ebenezer and Durga (2015) shows the different techniques in the picture below.

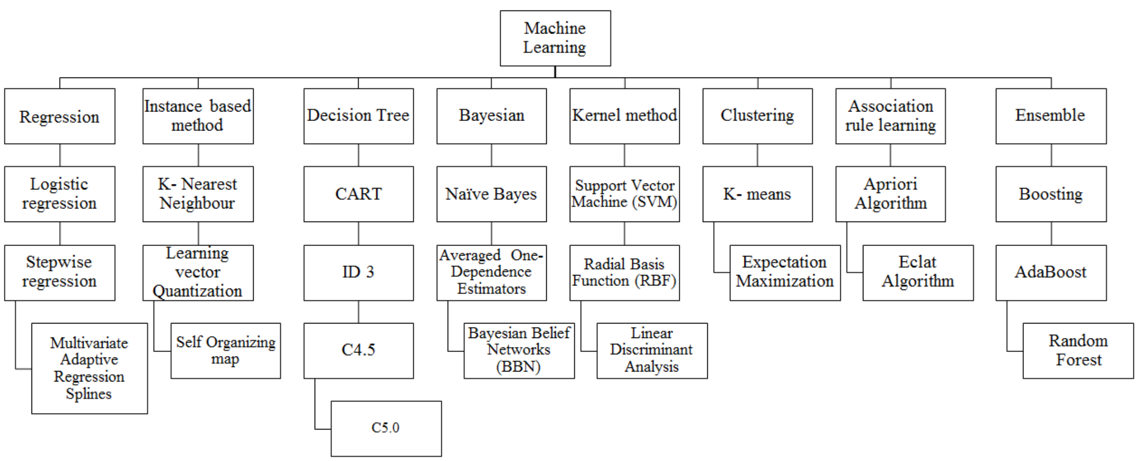

Figure 3: Machine Learning Algorithms (Ebenezer and Durga 2015)

2.1.5-Value Generation for Healthcare

Big data can generate value for healthcare organizations by providing cost savings or higher quality services. Although the healthcare sector was slow to use big data to create value compared to other sectors like information, communication companies or financial sectors, the healthcare sector is starting its digital transformation and creating value using big data. Evidence for this includes the growth of EHRs in hospitals; in 2012, 44% of hospitals in the US were using EHRs (Ward et al. 2014). The McKinsey Global

Institute estimates that the healthcare sector can generate $300 billion yearly by using big data, $200 billion of which could be created by reducing costs (Roski et al. 2014). Such value generation for healthcare can occur in many different ways, and every day new practices are discovered. This section provides several examples and explains main trends of value generation.

Big data can generate value in healthcare by supporting scientific advancement in medicine. Medicine is an evidence-based science meaning that scientific evidence from experiments are seen as more credible than expert opinions and testimonials. This is a clear indication that data and information are critical for decision-making in medicine. Therefore, big data can contribute significantly to scientific improvements in medicine. For example, processing EHRs to detect postoperative complications can help generalize the results of randomized trials for specific operations. Although data from EHRs cannot replace the randomized trials due to reliability and the lack of specific data per patient, it can complete the weaknesses that stem from limited numbers of patients in randomized trials. Like this example, there are many ways for big data to support these medical and scientific improvement (Murdoch and Detsky 2013).

Scientific knowledge in medicine is mostly in the form of scientific papers, as in many other scientific fields. Although the digitization of these papers helps professionals to access information and stay current in their fields, many physicians, researchers, and professionals struggle to reach relevant information. Big data analytics can help process all scientific papers and present them to professionals in a quicker, more understandable and relevant way. IBM Watson and the Memorial Sloan-Kettering Cancer Center are collaborating to develop a tool for supporting diagnoses and treatment options for cancer patients (Murdoch and Detsky 2013). These types of tools can process entire EHR data sets and scientific papers, and then propose the best treatments options for the specific needs of patients. As a result, knowledge dissemination about the best practices can diffuse at a much faster speed (Murdoch and Detsky 2013).

With the use of big data, professionals can access certain data that they could never have reached otherwise. This data is mainly sourced from self-generated data. For example, Kuziemsky and colleagues (2014) say that symptoms related to mental health problems like depression and schizophrenia can be detected by analyzing social networks usage data. Gittelman and colleagues (2015) also conducted an analysis using Facebook-like data with the purpose of public health surveillance. Their results using Facebook-like data were similar to those using traditional techniques for public health surveillance, with much lower costs and much faster results. These examples show how new data sources can use big data to provide better solutions for the advancement of medical knowledge and healthcare systems.

Big data technologies can also offer numerous improvements in terms of healthcare management and administration. For example, Ward and colleagues (2014) state that dashboards and control charts can improve healthcare facility processes and help management to control these processes. Using these tools, metrics like surgical site infections, remission rates, patient waiting time, or room utilization can be easily monitored and improved. The monitored metrics can be used to conduct patient flow analysis with the purpose of optimizing the patient experience and minimizing facility costs. Besides optimizing patient flows, big data can also be used to improve each process in the patient flow. For example, the first process for a patient entering to a hospital is triage, where the patient is assessed in terms of severity, followed by patient flow planning. Bates and colleagues (2014) state how big data technologies can improve triage process dramatically, thus improving the overall patient flow and hospital efficiency. They report two pilot applications in Kaiser Permanente Northern California, and their results indicate significant improvements. On the other side of the healthcare system, the insurance and payments side, Srinivasan and Arunasalam (2013) show how big data support fraud detection and therefore reduce costs for the overall healthcare system.

4P-Medicine

4P Medicine stands for Predictive, Personalized, Preventive and Participatory Medicine; this approach in medicine favors a proactive discipline rather then a reactive one. This is a trending approach that is supported by most scholars and physicians. 4P-medicine aims to keep people healthy and maintain preventative practices. This approach is centrally different than other systems like the American system which shows patients treated after becoming sick. This approach is not only about big data, but big data can contribute a lot in each of the four Ps. Using big data, one can use predictive analysis to intervene before any illness. EHR data and genomics data can be used to design personalized medicine. Using accurate predictions and personal information, preventive medicine can be used to keep individuals healthy. With communication platforms and data shared between patients and caregivers, patients can be active participants in making decisions about their health and lifestyle. This 4P approach is exactly that- an integral discipline that identifies one’s health and lifestyle as intertwined (Holzinger et al. 2015).

One example of predictive medicine is determining high risk, high cost patients.

Fifty percent of US healthcare spending goes to around five percent of patients. Identification of preventive measures for these patients can reduce cost significantly. Another example of cost reduction can again be done by predictive analysis of hospital readmissions. Readmissions are costly and one-third are reported to be preventable (Bates et al. 2014). Song and Ryu (2015) conducted an analysis using social network data in Korea in order to prevent and proactively detect suicide.

Personalized medicine is defined as "to match the right drug with the right dosage to the right patient at the right time" (Panahiazar et al. 2014). EHR can be combined with genomics data to personalize medicine for each patient. With the use of personalized medicine approach, adverse events can be prevented and side effects can be minimized. Diseases affecting multiple organs prove challenging for physicians and specialists to design to treatment options. With the knowledge coming from EHR and genomics data, physicians can better optimize treatments for these patients (Bates et al. 2014). Personalized medicine can greatly improve the quality of life for patients with multiple chronic illnesses. Considering their interactions with multiple specialist doctors and possible a number of daily pills, having a comprehensive personalized treatment can at least provide them with noticeable pill reduction or one daily pill.

Participation of individuals in their health management is critical to the success of 4P-medicine approach because predictive, personalized, and preventive aspects of the approach require volunteer data sharing and active participation by each individual of his or her own health management. Big data tools are crucial in supporting these goals. These tools should provide communications between parties related to individual health, including oneself and all the relevant information for everyone involved in the support of the patient’s health. One example of such tools is obviously EHR systems. They provide information to all and patients can easily communicate with their doctors.

Big data can provide other tools for participation of individuals. The self quantification movement is another example, which favors individuals monitoring themselves rather than the traditional way of healthcare professionals monitoring patients. This movement can provide valuable data for professionals to help patient decisions, and moreover professionals gain communication channels to educate people about their medical needs to support patient participation.

Another important tool for participation includes social media sites, some of which can be seen in the table below. PatientLikeMe.com is a platform where patients take active roles in their treatment process and help one another, particularly those with the same diseases. Hansen and colleagues (2014) report a number of examples from the literature related to the self quantification movement and social media sites, as the table below shows.

Table 2: Example Uses of Self Generated Data in Healthcare (Hansen et al. 2014)

Data type	How has it been used in health?	Examples
Quantified-self data (via devices, self-reporting, or sensors)	1-Engaged in the self-tracking of signs and/or behaviors as n=1 individual or in groups, where there is often a proactive stance toward acting on the information 2-Provides richer and more detailed data on potential risk factors (biological, physical, behavioral or environmental) 3-Allows data collection over potentially longer follow-up periods than is currently possible using standard questionnaires	1-Food consumption 2-Information diet 3-Smile triggered electromyogram (EMG) muscle to create unexpected moments of joy in human interaction 4-Coffee consumption, social interaction, and mood 5-Idea-tracking process 6-Use of rescue and controller asthma medications with an inhaler sensor (e.g. Asthmapolis) 7-Monitors blood glucose levels in diabetics (e.g. Glooko) 8-Psychological, mental and cognitive states and traits (e.g. MyCompass) 9-Physical activity (e.g. FitBit; Jawbone Up, RunKeeper) 10-Diet (e.g. My Meal Mate) 11-Sleep quality (e.g. Lark) 12-Medication adherence (e.g. MyMedSchedule)
Location-based information	1-Information derived from Global Positioning Systems (GPS), Geographic Information Systems (GIS), and other open source mapping and visualization projects 2-Provides information on the environmental and social determinants of health 3-Monitors for disease outbreaks near your location	1-Weather patterns, pollution levels, allergens, traffic patterns, water quality, walkability of neighborhood, and access to fresh fruit and vegetables (such as supermarkets) 2-HealthMap
Twitter	1-Assesses disease spread in real-time 2-Assesses sentiments and moods 3-Facilitates emergency services by allowing for the wide-scale broadcast of available resource, enabling people in need of medical assistance to locate help 4-Facilitates crisis mapping (e.g. where eyewitness reports are plotted on interactive maps. These data can help target areas for emergency services and additional resources) 5-Facilitates discourse on non-emergency healthcare (e.g. broadcasts of public health messages, quantify medical misconception)	1-Quantify medical misconceptions (e.g. concussions) 2-The spread of poor medical compliance (e.g., antibiotic use) 3-Trends of cardiac arrest and resuscitation communication 4-Cervical and breast cancer screening 5-Postpartum depression 6-Influenza A H1N1 outbreak (disease activity and public concern) 7-2010 Haitian cholera outbreak 8-Emergency situations from Boston marathon explosion
Health-related social networking sites	1-Facilitates sharing of personal health data and advice amongst patients and consumers 2-Monitors spread of infectious diseases via crowd surveillance	1-PatientsLikeMe 2-Disease surveillance sites which collect participant-reported symptoms and utilize informal online data sources to analyze, map, and disseminate information about infectious disease outbreaks (e.g. Flu Near You, HealthMap, GermTracker, Sickweather)
Other social net-working sites (e.g. online discussion board, Facebook)	1-Monitors how patients use social media to discuss their concerns and issues 2-Provides awareness of what the ‘‘person in the street’’ is saying	1-Side effects and associated medication adherence behaviors (e.g. drug switching and discontinuation)
Search queries and Web logs	1-Found to be highly predictive for a wide range of population-level health behaviors 2-Search keyword selection has been found to be critical for arriving at reliable curated health content 3-“Click” stream navigational data from web logs are found to be informative of individual characteristics such as mental health and dietary preferences	Google and Yahoo search queries have been used to predict epidemics of illnesses, such as: 1-Influenza (Google 2013) 2-Dengue fever 3-Seasonality of mental health, depression and suicide 4-Prevalence of Lyme disease 5-Prevalence of smoking and electronic cigarette use

Finally, Holzinger et al. (2015) consider 4P Medicine as the future of medicine and healthcare systems. They state that a good way of supporting this vision is so-called 'smart health environments'. With the proliferation of internet of things and the invasion of the world by sensors, concepts of 'smart cities' or 'smart buildings' are trending upwards. In general, these can be thought of as optimizing all operations of whatever SmartX may be: a smart city, smart building, smart environment. This optimization is done by using all the data generated by the sensors of SmartX. Holzinger thinks that healthcare will be part of this trend and it has to become smart. Therefore, all the hospitals, healthcare facilities and even patients' homes and environments will be 'smart', meaning that they will be optimized using the sensor data placed in these environments. Holzinger claims that smart health environments will be the enabler of 4P-medicine. Although this is a vision and interpretation, and whether it will happen or not is open to discussion. However, it clearly shows the potential effects of big data on healthcare and how big data can support 4P-medicine.

2.1.6-Challenges

Big data provides entrepreneurs with much value creation via data creation. The trend of digitalization is creating more and more data, and we have the tool to process this data. Lots of other sectors are using big data technologies extensively, and healthcare can examine these players, detect the best practices and copy them. However, the healthcare sector has some unique issues. These issues have to be examined and addressed so that big data can revolutionize healthcare.

2.1.6.1-Privacy and Security

Disruptive advancement of big data has brought serious concerns about privacy and data security. As millions of people represent the source of data generated and processed, there is a growing debate about how to secure this data and how protect individuals' privacy rights. The National Security Agency (NSA) whistle-blower Edward Snowden demonstrated the scandalous practices that violate privacy rights. Instances such as this increase the concerns among people and discourages them from using big data technologies (Bates et al. 2014). On the other hand, today more that 90% of money in the world is in digital forms. People actually do trust digital security and privacy enough to keep their wealth in digital forms. Although privacy and security concerns have to be addressed for the sake of big data in general, healthcare data holds a highly sensitive position among other data in terms of privacy and security. Certain personal health data are so sensitive that in the case of a leak subjects might prefer to suicide or face psychological issues.

Genetic data is one example of highly personal and sensitive data. Currently, the US federal government has a policy of making genome project results public as often as possible. However, there are rising concerns about the use of genetic data for fear of discrimination in employment or insurance (Ward et al. 2014).

Another issue concerns the use of EHR data for scientific research. Patient consent is currently necessary for each scientific research, a cumbersome process especially when large data sets are required. EHR data can also be used for managerial purposes, which also requires patient consent. While this consent also determines who can access the data, organizations might need big data specialist outside the organization to analyze this data. This creates another problem of who can access to the data. Healthcare organizations demand a general solution to this consent problem and the problem of who can access the data to make better use of EHR data. Although one may suggest that de-identification of EHR data as a solution, there are cases that show de-identified data can be re-identified (Ward et al. 2014).

Roski and colleagues (2014) offer cloud service providers as a solution to the technology aspect of the privacy and security concerns. Thanks to their expertise in big data and economies of scale, the cloud service providers can support the most advanced and recent data security and privacy technologies. They can also tag each piece of data with specific access rights for specific users. Their services might be superior to a single healthcare facility's capability due to limited budget and competence in big data technologies of the healthcare facility.

2.1.6.2-Policy and Regulations

As healthcare is a highly regulated sector provided by government in most developed countries, government policies and regulations about healthcare play an important role in exploiting big data technologies for healthcare. Government can play a central role in supporting data sharing and collaboration among healthcare and big data actors. Competitive forces might prohibit this collaboration and lead to suboptimal results for the whole society. Policies and regulation might, for example, require certain data pools that give access to all parties but limit each party's access to the source of the data in the pool. This could ensure privacy, data security and competitive advantages of private players (Roski et al. 2014).

Among other healthcare related regulations, privacy and security regulations about healthcare data hold a critical place to support the use of big data technologies in healthcare. As the development speed of big data is enormous, the regulations should also be evolving to meet the needs of people and healthcare players in terms of privacy and security. As explained above, privacy regulations might not be enough to protect personal data and at the same time, they can be impractical for healthcare organizations to make use of big data. As an example, privacy and security regulation is represented in the Health Information Portability and Accountability Act (HIPAA) of 1996 of the US. However, scholars say that the act does not address numerous issues becoming relevant as data becomes more linked. (Bates et al. 2014)

"The concept of consent implies a person's right and ability to control information about him- or herself and to impose limitations on its use and reuse by entities such as researchers and health care organizations." With current regulation about consent, researchers and managers need specific consents for each scientific research or managerial project. This concept implies a trade off between patients' privacy control and the ease of use of data for sciences and healthcare systems. Therefore, regulative authorities should balance this trade-off and constantly evolve regulations with development of big data technologies. (Roski et al. 2014)

2.1.6.3-Adoption (Incentive for Doctors)

With the development of big data technologies, organizations from all sectors consider data as their strategic asset. Therefore, it is crucial that management and other employees of any organization understand the importance of big data. However, organizational culture from healthcare players has been a barrier for the adoption of big data technologies. Murdoch and Detsky (2013) claim that there are no strong incentives for healthcare professionals to embrace big data technologies. Kuziemsky and colleagues (2014) examined the effect of big data adoption from the perspective of people, social, and organizational considerations. They state the challenges for organizations to adopt big data and propose solutions to overcome these challenges.

2.1.6.4-Data scientists for Healthcare: big data knowledge gain in healthcare

The trends that lead to big data also lead to high demand for data scientists. Healthcare organizations have to compete with high tech companies like Google, Apple, Facebook etc. to employ data scientists. Moreover, healthcare organizations need data scientist, who are by definition experts in mathematics and computer science, but also have healthcare domain expertise. This reduces the number of available candidates for healthcare organizations to employ for their big data projects. The healthcare organizations have to address this challenge and they should employ enough data scientists to create the big data culture within their organizations and collect the necessary knowledge of big data in healthcare. (Song and Ryu 2015; Roski et al. 2014)

2.1.6.5-Cooperation: integration, interoperability

There are different types of players in the healthcare systems like central hospitals, local hospitals, pharmacies, pharmaceutical companies, patients etc. Each of these actors have different types of data. Sharing this data can benefit all players in the ecosystem. However, there are other drivers that prevent data sharing, such as competitive force and privacy concerns. These obstacles should be address to make the best use of big data. (Song and Ryu 2015)

One of these obstacles is integration of data from different sources. The definition and use of standards are necessary for this purpose. These standards can also support interoperability between different systems of different organizations to obtain further cooperation. However, Luna and colleagues (2014) claim that integration and interoperability problems are mostly political rather than technical. There are already organizations that define standards for data in healthcare but widespread use of these standards is the problem.

2.1.6.6-Technological challenges:

With advancement of big data, amazing problems are addressed and very hard technical challenges are solved. Data infrastructure can be provided as a service, and these are just some examples of challenges addressed by big data. The source of each data can easily be tagged to address the challenge of source tracking. Data capturing from lab results to personal smart phones can also be done. Regardless, there are other technological challenges to be addressed in healthcare and some needed improvements (Roski et al. 2014; Luna et al. 2014).

One area that needs improvement is in EHR systems' data quality. Although there are standards that dictate certain quality of data in EHR systems, not all healthcare organizations are able to comply with these standard. Moreover, different physicians or nurses might enter data with varying quality within the same organization. Therefore, EHR systems should be improved to comply with the standards and to ensure the same quality of data entrance independent of the user. (Ward et al. 2014)

Another challenge in healthcare is computational algorithm developments for healthcare problems. Although big data offers valuable algorithms and analytical technologies, they should be applied to healthcare problems. Holzinger and colleagues (2015) give some examples of such challenges like context aware computing, cognitive computing, and stochastic computation.

2.1.6.7- Challenges in developing countries

Big data poses great opportunities for healthcare improvement in developing countries, where these countries can skip certain steps that developed countries went through when developing healthcare systems. Big data adoption in developing countries might have unique challenges that have to be addressed by keeping their unique conditions in mind. These can vary from corruption to infrastructure of electricity and internet (Wyber et al. 2015)

Internet access by patients can create a serious challenge in developing countries. Most developing countries have very high mobile penetration rates, allowing mobile phone data to be a source for big data projects. Unfortunately, they may be limited in terms of other data when compared with developed countries where citizens create enormous amounts of data from various sources daily. Finding data scientists to employ might also be really challenging in developing countries but there are non-profit organizations like Datakind that can be used for big data organizations. Alternatively, telecommuting data scientist can be employed (Luna et al. 2014).

2.1.6.8-Public training: Misuse of social media

One very important part of the healthcare system is the patients (people). As explained in the 4P-medicine approach, people are becoming more participative in healthcare systems and decision making processes about patient health. This situation requires people to be trained about health related topics. Internet and big data technologies create new channels for people to educate themselves. This is a great opportunity for healthcare professionals to train people about their health.

These new channels should be wisely used and controlled. With the increase of self-generated content, the misuse of these channels might occur. For example, pro-anorexia activists are defending this disease as a life style using social media sites. One can find this content when looking for healthy eating habits. Due to their popularity, these sites can have higher rankings on a Google search because Google's algorithm uses popularity as a criterion for having higher rankings. Another dangerous movement is the anti-vaccination movement which denies the efficacy and safety of vaccines. Although distinguishing false information from true information is a general challenge of the internet, it becomes more sensitive and important when related to healthcare (Fernandez-Luque and Bau 2015).

2.2-Social Networking Sites in Healthcare

This part of the report explains how social network sites (SNSs) usage data engage with the healthcare sector. A lot of studies have been found in the field of social networking and innovative healthcare applications, but there is limited research about utilizing Social Networking Sites in healthcare sector.

2.2.1-General Description of Social Networking Sites

According to Boyd and Ellison (2007) the definition of social network sites is "web-based services that allow individuals to construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view and traverse their list of connections and those made by others within the system". The system and terminology of created connections can change from site to site.

Social Networking is a tool used for relationship establishments which are generally between strangers and not so close people. These piles of new relations among people in these new networks create possible high popularity and growth potential on these sites. Before Social Networking Sites there were many examples of computer mediated communication (CMC) tools which were creating contacts among people but their efficiency was not very good. The key difference of social networking sites from other communication tools was not only for making new friendships; rather that they could give users the chance to join new social networks (Boyd and Ellison 2007). There can be also another stage of these new relationships by meeting in real life with these new “social network friends.” Actually, this was not the goal of social networking directly and these meetings are frequently between “latent ties” which are technically possible but not activated (Haythornthwaite 2005). There are also several views about social networking sites where people do not look for only new people or creating a new network with strangers around them. They want to communicate with their social environment that is composed by people who are already in their lives through several relational bonds just like friends of friends or co-workers at same company (Philips 2007). Therefore, the organizational structure should be very well planned and complicated to make it working social network in digitalized world.

2.2.2-History of Social Networking Sites

The early predecessors of SNSs started with bulletin board systems (BBS) in the late ‘70s and early ‘80s; online systems based on codes sharing and letting users communicate with other users by posting messages, and downloading files and games. The system access was provided by a modem which works through a telephone connection. Bulletin board systems were managed by technology experts who wanted to create a social area for similar people that love and interested in those early computers just like themselves. They wanted to gather all similar technology lovers together through these BBSs (Digital Trends 2016). The system had some limitations about long distance calling rates which were expensive and connection was not viable. This made Bulletin Boards generally locally based and meet-up points were for local people. They started to socialize with each other first through BBSs. Modem technology was improving so fast in early 90s. They were offering low prices with high speed modems to ease online services which created a golden age for BBSs in the early 1990s. According to InfoWorld (2016) magazine, BBSs were estimated to be 60,000 and user numbers were more than 17 million in USA in 1994 alone. Later, the launch of dial-up internet service and mosaic web browsers provided user-friendly solutions to people. BBSs lost their popularities by the end of 1990s because of the developments of new technologies and advanced social networking sites. BBSs were the first online platforms for connecting people in a network.

As we defined social network sites, a complete example of social network sites started in 1997. Its name was "SixDegrees.com" which let users create profiles, listing friends and, later in 1998 also could see each others' friend lists. But all these new features were not the website's direct invention. These concepts started with some other online communication sites like dating websites and other chatting web pages like AIM and ICQ (Boyd and Ellison 2007). The base mechanism, known as the web of contacts, consisted of lists of friends and friends of friends, although those friends were not visible to others. Another platform is called as "Classmates.com" that gave people the chance to find their high school or college friends and permitted users to see other members' friend affiliated lists without user profiles (Boyd and Ellison 2007). SixDegrees became the first platform offering all these features under one web page. SixDegrees defined its function as a bridge between people create connection through sending message, creating profiles adding to friend lists. SixDegrees became so popular and attracted 3.5 million users. Nevertheless, SixDegrees was not a sustainable business and closed in 2000. According to its founder, SixDegrees was simply ahead of its time. A key point here is that the United States Patent No.6,175,831, or the ‘Six Degrees Patent,’ invented by Andrew Weinreich. The patent defined a social network as the ability to see unacquainted people through friends and acquaintances, made possible by indexing relationships into a single database.

When internet connection started to spread all around the world, people started to discover new interests. These interests were not only socializing or creating networks but sharing ideas and finding similar people with common interests. Aside from SixDegrees, there were many community tools from different countries. These supported various profile types and publicly articulated friendships. One example of these community tools was Ryze.com which was launched in 2001. Its aim was to help people to strengthen their business networks. “*Ryze’s founder explains that he first introduced the site to his friends who are primarily members of the San Francisco business and technology community, including the entrepreneurs and investors behind many future SNSs”* (Boyd and Ellison 2007). Because of their close personal and professional relationships, the people behind “Ryze”, “Tribe.net”, “LinkedIn”, and “Friendster” were knitted to each other and supported each other without getting in one another’s way. Among these four platforms only LinkedIn succeeded as a popular and strong business service, while Friendster became most popular at one point but later on failed (Boyd and Ellison 2007).

After 2004, teenagers started to participate in social network sites with MySpace. As young people started to register they encouraged their friends to join. MySpace changed its policies to adapt these new users' profiles to its network. Traditional media channels didn't mention about the development of social networking sites until mid 2004. Few others noticed the site's growing popularity. Then, in July 2005, News Corporation acquired MySpace for USD $580 million (BBC News 2005). Mainstream media focus was attracted to Social Networks. MySpace attracted the majority of media attention in the U.S. and abroad. A new era was starting and SNSs were becoming a global phenomenon. Different SNSs were launching, growing and expanding quickly in US and the rest of the world. For example, Hi5 became popular in Latin America and Europe. Bebo spread in the United Kingdom, New Zealand, and Australia. Also, previously popular communication and community services began showing SNS features. For example, in China the QQ instant messaging service suddenly became the largest SNS worldwide when it added profile and friend visibility (Leow 2008).

The Facebook:

A new type of SNS was born in 2004, that launched initially for distinct college networks usage only, before expanding to a bigger population. It was called "The Facebook" as a Harvard based SNS. The system could accept only users with a harvard.edu email addresses. As Facebook began spreading its network to other schools, those users had to have university email addresses associated with those institutions. This requirement provided the site relatively closed and contributed to users' perceptions of the site as an intimate, private community. Later in September 2005, Facebook decided to change its structure and include high school students. On the other hand, professionals inside corporate networks were always required to have corporate e-mail addresses (Philips 2007). Unlike other SNSs, Facebook users were not able to make their full profiles public to all users. Facebook differentiated by allowing independent developers to create “applications” which let users to personalize their profiles and spend time on Facebook for other tasks, such as creating movie lists and reading travel stories.

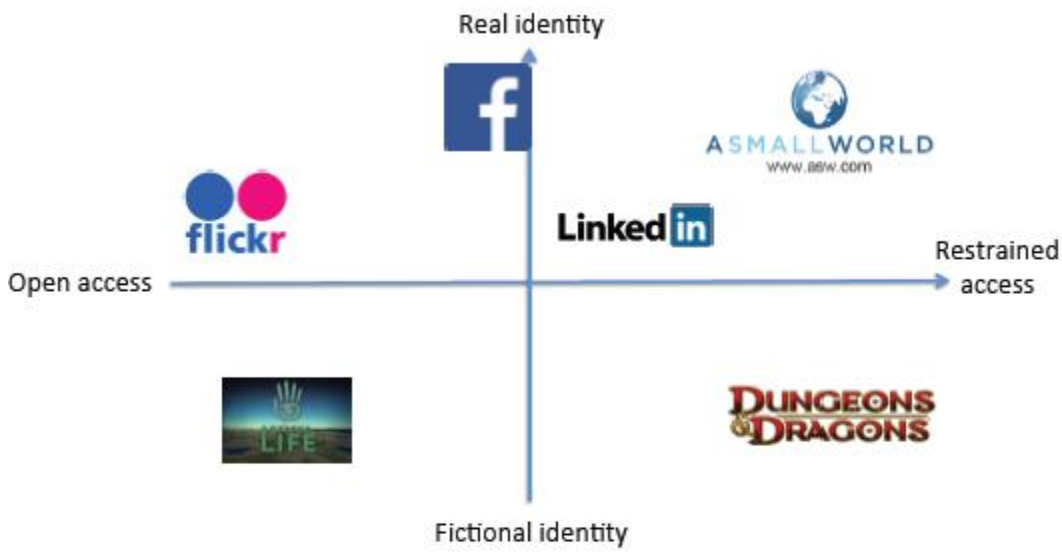

Figure 4: Positioning of Facebook

Facebook reached 12 million users and rejected an offer of USD$ 1 billion from Yahoo when it tried to acquire the company in 2006. 2010 marked another big milestone concerning privacy settings change. This change included "pre-approved" third-party websites to access users' personal information. For example, when users visit external websites, websites will already know the user’s name, birthday, friend lists and any other data that each user shares on Facebook (Rubin 2005). On the business side Facebook also made big steps in 2012 as the biggest technology based company IPO in the world. In 2014 mobile application of Facebook became the leading money resource of the company with right advertising strategies. According to Facebook's data, more than one billion active users have profiles and log-ins on Facebook.

Social Media Growth 2006-2012

Year	Facebook	Twitter	LinkedIn	WordPress	Tumblr	Google+	Pinterest
2006	12,000,000	1,000	8,000,000	600,000	0	0	0
2007	50,000,000	750,000	15,000,000	2,000,000	170,000	0	0
2008	100,000,000	5,000,000	33,000,000	4,300,000	1,000,000	0	0
2009	350,000,000	75,000,000	50,000,000	8,000,000	2,000,000	0	0
2010	600,000,000	145,000,000	75,000,000	11,100,000	7,000,000	0	10,000
2011	800,000,000	300,000,000	135,000,000	50,000,000	38,000,000	90,000,000	11,700,000
2012	1,000,000,000	500,250,000	200,000,000	60,830,000	86,800,000	400,000,000	25,000,000
CAGR	109.00	507.47	71.00	120.43	248.03	344.44	4,900.00

http://www.dstevenwhite.com

Figure 5: Social Media Growth

High growth rate of Facebook created some opportunities for companies to invest time and money in promoting and advertising on Facebook. The popularity of Facebook can be seen in the figures and graph below. The figures show the most popular SNS of each country. The graph shows number of monthly active users of different SNSs.

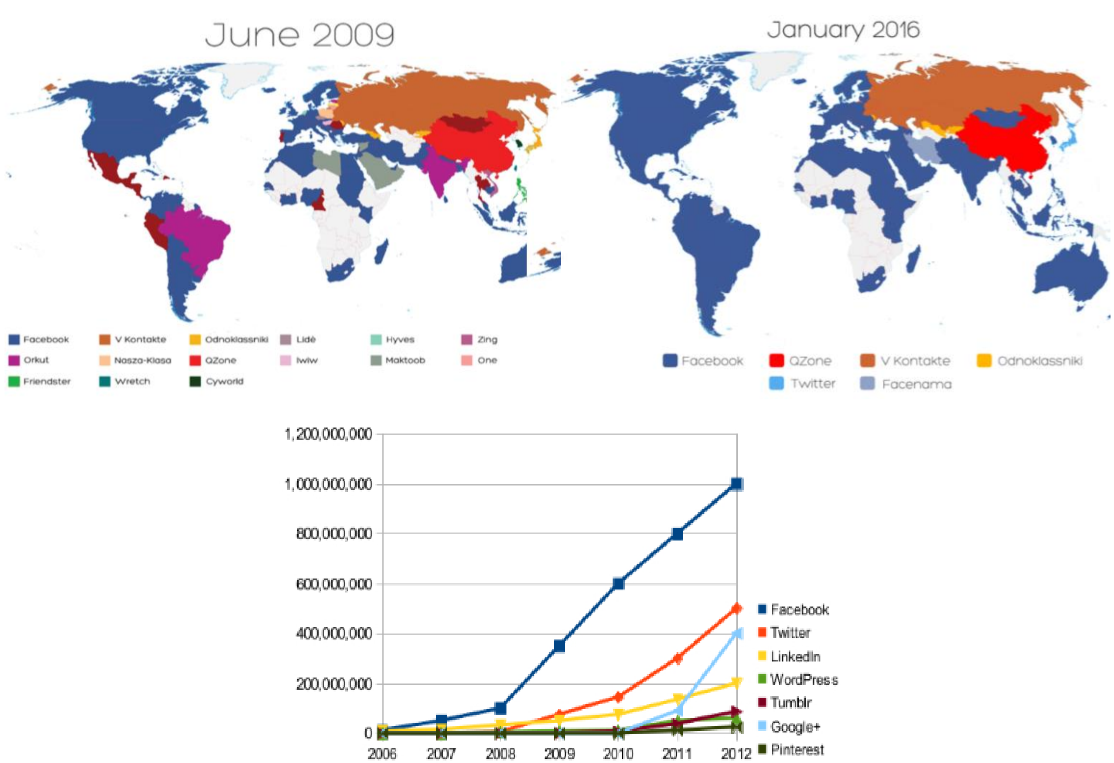

Figure 6: Growth of Facebook (Alexa 2016)

The recent developments in SNSs shows a change in the organization of online communities. While websites related to the communities of interest still exist and succeed, SNSs are primarily organized around people, not "interests" (Wellman and Berkowitz 1988). The diagram below indicates the user centric structure of the networks in the most recent SNSs.

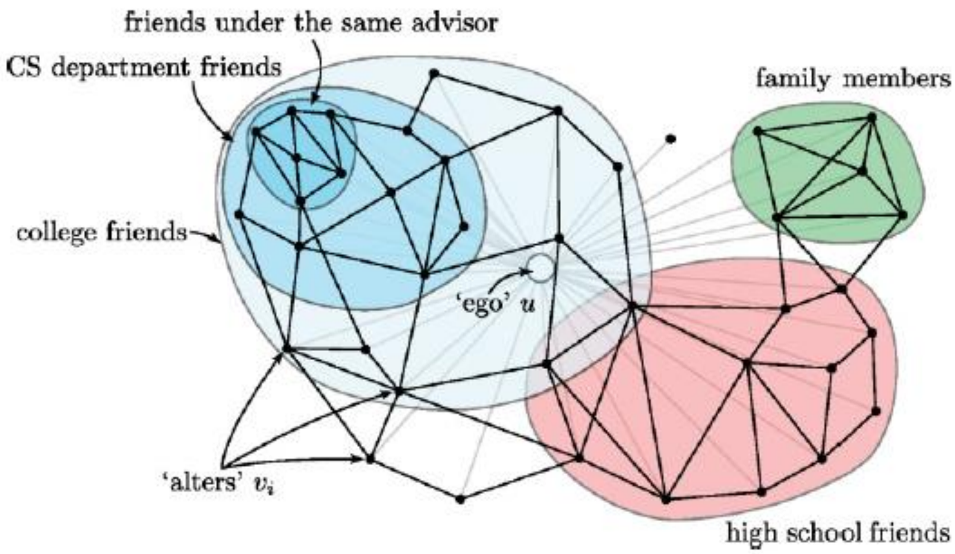

Figure 7: User Centric Structure of The Networks (Wellman and Berkowitz 1988)

2.2.3-Individual User Behavior

Millions of humans on Earth are living part of their lives on SNS, such as Facebook, MySpace, Twitter and LinkedIn. In 2010, people spent one fifth of their online time on SNSs or blogs (Bilton 2010). Lenhart and colleagues (2010) reported that 73 of teens, 72% of young adults aged between 18-29, and 40% of adults older than 30 in the world have a profile on an SNS. Their research showed a dramatic increase in the number of older users. Social Networking Sites started to attract academicians and researchers starting at the end of l990s. Particular companies include Myspace and later on Facebook, Twitter and Instagram attracted a large number of scholars' attention. The scholars are from various disciplines and interested in a range of topics related to SNSs. Some examples include self disclosure (Nosko et al. 2010), online friendship (Henderson and Gilding 2004) and online dating (Rosen et al. 2008). Early researchers made great contributions to the study of behavioral patterns of individuals in SNSs. Some examples are the dynamics of online group interactions and the relationship between the participation in an online community and an individual's off-line life. These points are important to analyze the online behaviors of people in the internet era.

Some frameworks and empirical studies about individual SNS usage motivations have been developed in order to understand the people who will use the service, as well as the goals and personal incentives they have for doing so. Brandtzæg and Heim (2009) empirically looked for individuals' motivations for SNS behaviors and usage, by performing a quantitative content analysis of 1,200 qualitative responses from social networking site users in Norway in 2007. Their main conclusion related to the reasons of SNS use was that the most important reason is to "meet new people" (31%); the second one was to "keep in touch with their friends" (21%); the third one was "general socializing" (14%); followed by "Access to information" (10%). Other motivations they found include debating (6.5%), free SMS (3.5%), time killing (3.5%), sharing content (3%), unspecified fun (2%), profile surfing (1.5%), family (1%) and others (3%).

The Uses and Gratifications (U&G) theory is used for explaining "why" some media behaviors occur. This theory is basically an audience-centered approach to understand mass communication. It explains why and how people actively seek out various media channels to satisfy their specific needs. According to the U&G theory there are four main motivational needs. Brandtzæg and Heim's (2009) conclusions fit the U&G

theory quite well: 1- information (information, sharing and consuming content, debating), 2- entertainment (unspecified fun, time-killing, profile surfing), 3- social interaction (socializing, friends, family, new relations, free SMS), 4- personal identity (profile surfing).

Mainly research results show that there are two main uses of online social networks. The first use is that users can find others with similar interest, ranging from romantic relationships to social networks (Correa et al. 2010). Another use is to maintain already created social connections (Boyd and Ellison 2007). Most users visit the sites to keep in touch with people they already know (Lenhart et al. 2010). Researchers found that many relationships first formed online resulted in real-world contacts (Ross et al. 2009). After getting connection through SNS, the relations could go deeper and longer than the real life face-to-face methods made possible (Mckenna et al. 2002). Such online interactions also generated more self-disclosures and fostered deeper personal questions than did face-to-face conversations (Nosko et al. 2010; Tidwell and Walther 2002). Because this kind of conversation did not have restrictions governing typical face-to-face conversations, those engaging in online conversations were able to ask deeper personal questions (e.g., sexual orientation) without offending each other (Tidwell and Walther 2002). As social network sites support interpersonal interaction, SNS use may be a function of personality (Correa et al. 2010).

SNSs usage is related to personal innovativeness to information technologies (IT), although the innovativeness effect on SNS usage has been supported by little research. Innovativeness has been accepted as a characteristic specification because it is possessed to some degree by everyone (Manning et al. 1995; Midgley and Dowling 1978; Midgley and Dowling 1993). Innovativeness can be socially influenced and different across a person's life cycle (Hirschman 1980). As a continuous variable, innovativeness is normally distributed within a population and generalizable across ICT products (Cowart et al. 2008). During their efforts to understand the process of user acceptance to ICT innovations, the personal innovativeness scale developed by Agarwal and Prasad (1998) is a widely used scale measurement. There are few empirical studies showing a significant relationship between the Personal Innovativeness on IT (PIIT) scale and behavioral intention (Agarwal and Karahanna 2000; Lu et al. 2005; Thompson et al. 2006). ICT innovativeness can also have a direct effect on SNS use: people with high scale in ICT innovativeness may have high SNS use.

The other point that influences the social networking experience is multitasking, a term describing the activity of performing different media tasks at the same period of time. Today, there are various media technologies (e.g. tablets, smartphones etc.) so media multitasking has been an important habit in the lives of Internet users. Media multi-tasking refers to engaging in two or more simultaneous media activities. Media multitasking needs a lot of cognitive effort and overlapping resources (Vega et al. 2008). For instance; working or studying online, chatting with friends over Facebook, listening to music or playing games online at the same time. In media multitasking the key element is switching between tasks that require overlapping cognitive processes. The experience of media multitasking and its essential mental habit of dividing and switching attention has significant implications for the way people socialize with others, reason and understand the world (Vega et al. 2008). But it should not be confused with traditional multitasking, which is typically conceptualized as performing two or more tasks at the same time (Jeong and Fishbein 2007). For example; a housewife can cook, watch TV and talk with her husband simultaneously, which can be defined as multitasking in a traditional meaning. But it is not media multitasking because there are no online media activities. The other difference between the two is that traditional multitasking, such as listening to music while jogging, requires minimal cognitive effort.

Research on media multitasking has generally focused on people's productivity, work efficiency. This research field tries to understand the psychological mechanisms behind the effects of media multitasking on productivity and efficiency of people (Rubinstein et al. 2001; Vega et al. 2008). Some studies have shown that task-switches in multitasking damage an individual's performance (Rubinstein et al. 2001). The challenging part of task switching is cognitive control. Cognitive limitations of a person cause the "cognitive bottleneck" that leads people to perform slower and with reduced efficiency under multitasking conditions (Dux et al. 2006). Researchers found that while multitasking people completed all the tasks in a longer time than if they were performed one at a time, their performance was also worse. According to young users, however, it makes little sense not to media multitask while using a computer because "computers are naturally multitasking devices" (Baron 2008). On the other hand, young generations raised with the technology rarely notice a degradation of performance by engaging in media multitasking (Baron 2008). Empirical studies tell that people use SNS in the environment of media multitasking (Morpace Omnibus Report 2010). IT evolution enables media multitasking to improve the online experience, and media multitasking is related to the heavy usage of SNS among young people.

SNSs permit their users to follow streams of posts generated by hundreds of their friends and acquaintances. Users' friends generate overwhelming volumes of information so people need to organize their personal social networks to cope with the 'information overload'. One of the main mechanisms for users of social networking sites to organize their networks and the content generated by them is to categorize their friends into what we refer to as social circles. Practically all major social networks provide such functionality, like 'circles' on Google+, and 'lists' on Facebook and Twitter. Once a user creates his or her circles, they can be used for content filtering (e.g. to filter status updates posted by distant acquaintances), for privacy (e.g. to hide personal information from coworkers), and for sharing groups of users that others may wish to follow. Currently, users in Facebook, Google+ and Twitter identify their circles either manually, or in a naive fashion by identifying friends sharing a common attribute. Neither approach is particularly satisfactory: the former is time consuming and does not update automatically as a user adds more friends, while the latter fails to capture individual aspects of users' communities, and may function poorly when profile information is missing or withheld.

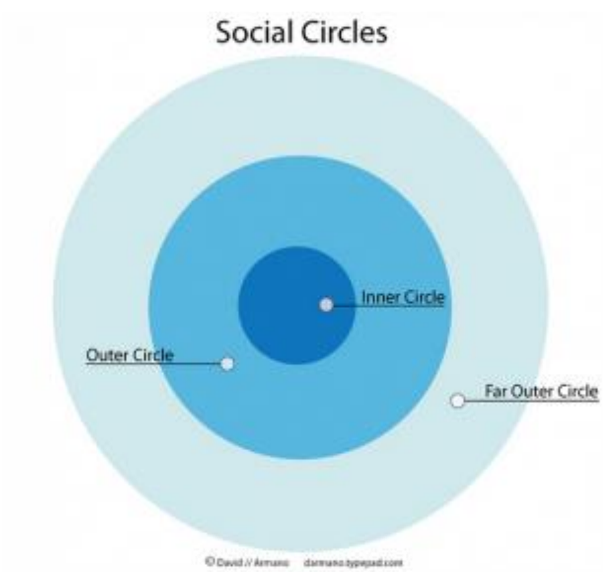

Figure 8: Social Circles on SNSs

2.2.4-Social Networking Sites Use in Healthcare

Substantial growth rate of SNSs provides golden opportunities for healthcare sector. Some of the opportunities are already taken by the current players of the healthcare sector. Other opportunities are yet to be taken but there are certain challenges to be addressed before. Current status and future possibilities of SNSs use in healthcare sector will be explained in the following parts of the report.

Healthcare Services via SNSs

There is a severe shortage of doctors, nurses, health workers and drugs in a large number of developing countries. Many patients never see a doctor or visit a clinic and those who do visit one often do not receive the care and treatment they deserve due to lack of resources. Thousands of people, mostly children, die from mistreatment (and sometimes from no treatment) of illnesses such as diarrhea, dehydration, malnutrition and malaria. There are several areas in developing countries where the closest qualified doctor is hundreds of kilometers away. Social networking sites can be used to bridge this barrier with a qualified doctor communicating directly with patients or with a standby medical representative of the area (Belbey 2015). Patients can relay the symptoms they are experiencing and a doctor can provide a diagnosis via a social network site. The model where the doctor is physically present is definitely ideal as they can physically examine the patients, but the social networking model is better than nothing at all.

Providing Healthcare Information via SNSs

Health discussion web pages may or may not provide information about how to obtain services, and improve access to services by helping initiate contact with the healthcare system. Farther, sharing personal health problems with other people who are empathetic and supportive can provide emotional and instrumental supports or can cause bad reactions, especially in mental illness (Link et al. 1991; Pescosolido et al. 2010). The response of active networks in the face of illness is hypothesized to have an important influence on recovery, and some empirical research provided reasonable evidence to support this link (Gallant 2003; Pescosolido 1998; Thoits 2011).

SNSs give chance to people to exchange information about their physical symptoms, clinical diagnosis and treatment options, adverse treatment effects, experiences with doctors and hospitals and opinions about their quality (Blumenthal 2011). Patients are using social networking to access and contribute health information. People living with chronic illness and disability use SNSs to share their expertise in assessing, combining and using information specific to the chronic problem. Social networks give a new prospect for patients to assemble health information, relatively free from the constraints of traditional health care (Griffiths et al. 2006). However, the key point about health information from social networks currently complements traditional sources rather than substituting them.

Social networking sites can be used as a platform to send messages in favor of public health and behavioral change campaigns, information delivery to health workers, and to send and receive data on disease incidence, outbreaks and public emergencies. Healthcare organizations use SNSs to engage with their patients and increase their brand image.

Obtaining Information About People via SNSs

Huge amount of data is generated by SNSs and an important portion of the data is related to healthcare (Hansen et al. 2014). The data contains valuable information about people related healthcare. The information obtained from SNSs' data can be related to public in general or individuals. As an example to the information related to public, it is possible to conduct public surveillance analysis using the data from SNSs. On the other hand, individual data on SNSs can be used for patients' follow-ups, increasing customer engagement for hospitals. One important and valuable use of individuals' data on SNSs is that diagnosis of mental health problems can be supported with SNSs' data (Kuziemsky et al. 2014). To be able to obtain useful information from SNSs data, advanced big data technologies are necessary. Social network mining is the field that specifically studies extracting useful information and knowledge from SNSs data.

Social networks are typically conceptualized as graphs comprising of nodes and links, where the nodes represent individuals (network users) and the links communications (traffic). These communications often take the form of text (emails) but can also be files (photographs, movies, etc.). Social network mining is the process of analyzing and extracting useful information from social networks (Nohuddin et al. 2012). Social network uses theories and methodologies from different disciplines such as computer science, data mining, machine learning, sociology, ethnography etc. It comprehends the tools to formally measure, model, and mine significant information from large-scale social network data.

Opinion Mining is the process of detecting, extracting and classifying opinions, sentiments and attitudes about different topics expressed in textual input (individual posts). It can be helpful on observing public opinion regarding political movements, understanding consumers, health surveillance of populations etc. Social networking sites provide the platform for widespread sharing of ideas and encouraging the public towards group discussions with open views. Social networks provide better means to quick responses and feedback on different global issues in the form of textual posts, news, images, and videos (Ravi and Ravi 2015). Thus, SNS's data can be used to understand people's opinions and behaviors, market patterns, and trends of society. For instance, Twitter has 255 million monthly active users and it oversees 500 million tweets every day. Thus, it serves as a good resource to extract heterogeneous opinions published by individuals from varied societies for different purposes like improvement of quality of products and services, prediction of consumers' demand and taste etc. (Ravi and Ravi 2015).

Various steps are needed to perform opinion mining from given data, since the data for opinion mining is coming from several resources in diverse formats. Due to wide availability of various online resources, data acquisition is highly subjective to the type of media, data format supported by media, and the type of analysis needed to perform. Some social network sites like Facebook, Twitter made their Application Programming Interface (API) available to collect public data from their sites. Twitter has provided Twitter REST API to obtain static data like user profile information, and Streaming API2 to access streaming data like tweets. Similarly, Facebook has made Facebook Graph API4 available. Raw data acquired from various sources often need to be pre-processed before launching a full analysis. Some popular preprocessing steps are: tokenization, stop word removal, stemming, parts of speech (POS) tagging, and feature extraction and representation. Tokenization works by breaking a sentence into words, phrases, symbols or other meaningful tokens by removing punctuation marks. Stop words do not contribute to analysis and hence are dropped during preprocessing step. Stemming is the process to bring a word into its root form, while ignoring other forms of the word. POS tagging is performed to recognize different parts of speech in the text. It is quite essential for natural language processing. Sentiment classification is performed according to syntactic and stylistic features such as word-length distributions, vocabulary richness measures, character and word level lexical features, and special character frequencies. Later, subjectivity classification deals with the detection of ‘‘private states’ - a term that encloses sentiment, opinions, emotions, evaluations, beliefs and speculations. The problem of distinguishing subjective versus objective instances has often proved to be more difficult than subsequent polarity classification. Polarity classifications are basically a sentence is expressing positive, negative or neutral sentiment towards the subject. As a results of these steps, opinion mining tries to extract public opinions on a certain topic. Together with social network mining, these two fields of data mining are essential to obtain information about people from SNSs data.

2.2.5-Challenges

Privacy of users is one of the biggest challenges of SNSs. Preibusch and colleagues (2007) argued that the privacy options offered by SNSs do not provide users with the flexibility they need to handle conflicts with network friends who have different conceptions of privacy. They suggested a framework for privacy in SNSs that they believe would help resolve these conflicts. SNSs are also challenging legal conceptions of privacy. Hodge (2006) argued that the fourth amendment to the U.S. Constitution and legal decisions concerning privacy are not equipped to address social network sites. The legality of this hinges on users’ expectation of privacy and whether Facebook profiles are considered public or private.

Another main concern related to patient's privacy in the healthcare industry is the legal issues, country-specific laws and legislations. Researchers have investigated the potential threats to privacy associated with SNSs. US Health Insurance Portability and Accountability Act (HIPAA) outlines guidelines for securing personal medical data. According to HIPAA, doctors can use patient data without their consent only for three purposes: "treatment, payment or healthcare operations". HIPAA does not actually prevent hospitals from using public networks, if patients give consent to their physicians for communicating over the open Internet. The concerns about complying with HIPAA is one reason of the use of social media in healthcare has not taken off quickly. Although a patient could give consent to have his or her medical information distributed outside the closed hospital system, HIPAA requires that hospitals save it as part of the official medical record because that information was used for decision-making purposes. As a result, all the related information even written messages and mail should be recorded and copied in patients' medical records. It is cumbersome and expensive to have each patient consent and save all information related to patients. Some companies like Kaiser, Deaconess and Geisinger Health System keep their EHRs "locked" behind firewalls, not because HIPAA says they have to but rather to manage their HIPAA compliances efficiently (Health Information Privacy 2015).

The other question is also arising from some providers' use of video and social media to transcend geographic barriers to deliver care. Healthcare providers will use patients e-health applications that is a newly born and there are also large and yet unanswered legal questions, such as what standards of care apply to this new e-health environment. Another issue besides standards is patients' data protection in e-health applications. The processes of e-health applications should be standardized just like traditional health care standards. Experts think an entirely new regulatory structure is needed to support the high-tech transformation of healthcare systems (Bates et al. 2014).

Although SNSs provide cheap and effective ways of informing societies about health related topics, the spread of misinformation is also equally cheap and effective. Fight against misinformation about healthcare should be done by governments together with healthcare organizations and workers. Dangerous examples of misinformation movements on SNSs are pro-anorexia activists and anti-vaccination movement. These movements advocated their claims even though they were totally against scientific evidence. It is possible for such movements to be more popular among people than their scientifically supported counterparts (Fernandez-Luque and Bau 2015).

2.3-Child and Adolescent Psychiatry

Child and adolescent psychiatry is relatively new branch of psychiatry. It has emerged in last 30 years. At the beginning of the 20th century, Lightner Witmer started the first psychiatry clinic to treat children with learning disabilities. William Healey founded the first child guidance clinic in Chicago in 1909. By 1933, the number of child guidance clinics were 42 in operation at different hospitals, schools, and universities. It was believed in the early 1900s that the reason of children's problems could be found in the parents and the family (Horn 1989). In 1948, 54 child guidance clinics came together to form the American Association of Psychiatric Clinics for Children (AAPCC) (Wilmshurst 2004).

John Locke, the 17th-century English philosopher, suggested that children came into the world as a blank paper and it was the parents' responsibility to fill the paper with the proper environmental controls and discipline. By contrast, the 18th-century French philosopher Jean-Jacques Rousseau emphasized on heredity and described the child as a flower that would grow and develop naturally in a laissez-faire approach (Wilmshurst 2004).

Most psychologists and psychiatrists think that the interaction of both heredity and environment is important in children's development. Scholars and professionals were involved in intellectual assessments of children psychiatry disorders for classification into several categories. By 1918, abnormal behavior in children continued to be interpreted from the adult psychiatry point of view. Thus, childhood mismatches were described in adult psychiatry terms and treated with adult treatment methods (Peterson and Roberts 1991). From mid 1930s, child guidance clinics were firmly reinforced in linking child problems to adult problems. Later in 1970s, several scientific journals have emerged that were exclusively dedicated to research about child and adolescent mental concerns. The most reputable ones were Journal of Clinical Child Psychology, Journal of Abnormal Child Psychology, Journal of the American Academy of Child and Adolescent Psychiatry, Journal of Child Psychology and Psychiatry and Allied Disciplines. In the mid 1980s, the field of clinical child psychiatry moved to evolutionary stage of development with the developmental psychopathology (Sroufe and Rutter 1984). Psychopathology emerged as an offshoot of developmental psychology, complete with its own journal, Development and Psychopathology. Inside this framework, atypical behavior is characterized as diverging from the normal developmental progress (Cicchetti and Toth 1998).

Although most professional skills and competencies, which are required to recognize normal from abnormal behavior, are shared by clinicians who serve adult and child populations; there are several unique skills and competencies required to recognize abnormal behavior of child population. Therefore, these two populations are considered as the subjects of different clinical fields. Deciding if a behavior pattern is normal or abnormal requires a fundamental understanding of behavior expectations and the range of behaviors that forms the broad limits of the behavior expectations. In order to find if a behavior is outside of the normal range, clinical judgment is often based on the decision making strategies. One way of measuring behaviors compared to normal expectations, is the use of "the four Ds" as a guideline to evaluate the behavior: deviance, dysfunction, distress and danger (Comer 2013). The use of the four Ds can provide helpful guidelines in determining normal from abnormal behavior in the following ways:

Deviance: The degree that behaviors are diverse from the norm must be examined. it can be assisted through the use of interviews, observations, symptom rating scales or more formal psychometric tests such as personality assessment.

Dysfunction: After disorder is diagnosed, the relative impact of the disorder on the individual's behaviors must be determined.

Distress: The degree of distress that the disorder causes must be evaluated. Children often have difficulty in articulating feelings. This may give information to the clinician in evaluating the distress.

Danger: It must be examined that if a given behavior creates a risk for the individual in means of self-harm or harm to others.

Clinical decisions are based on measures of the intensity, duration and frequency of a behavior relative to the standard (Wilmshurst 2004). Also, determining if a behavior is pervasive in different situations can also provide information regarding the nature and severity of the behavior of concern.

The ability to recognize normal from abnormal behavior and to select developmentally appropriate interventions can be guided with various theoretical frameworks. Different theoretical views can provide the clinician various guidelines.

Main perspectives are:

-Neurobiological and physiological theories are related to the impact of biological and genetic factors on individual differences.

-Behavioral theory is based on the fundamental faith that behavior is shaped by associations resulting from positive support and negative punishment consequences.

-Cognitive theorists are concerned with the relationship between thoughts and behaviors. They emphasize on how faulty beliefs in children can lead to abnormal behaviors such as aggression, depression, anxiety etc.

-Theories of Parenting and Family Systems Theory are related to parenting styles that impact child behaviors for better or worse. (Baumrind 1991)

The assessment process of a person includes examining individual differences, diagnosing signs and symptoms that are suggestive of specific mental disorders. The aim of diagnosis is to define the problem within the context of other known behavioral problems or disorders for the purposes of being able to bring on clinical knowledge regarding potential etiology and treatment alternatives. The initial purpose of an assessment is to diagnose the nature of the problem in order to offer the most appropriate treatment. The assessment process and diagnosing are done by following a classification system of diagnosis.

The most widely used diagnosis classification system in the United States is the American Psychiatric Association's Diagnostic and Statistical Manual of Mental Disorders (DSM). The International Classification of Diseases (ICD), published by World Health Organization, is the most commonly used system in Europe. Both systems are based on a categorical approach which defines discrete and mutually exclusive categories. In such approach, a given disorder can only be present or absent. Clinicians use these classification systems to evaluate the symptoms of a person in order to decide if the person has any given disorder. The DSM was first published in 1952 and the latest version, which is DSM-5, was published in 2013 (Wilmshurst 2004).

The process of clinical assessment can be done in several ways with different approaches and instruments based on the nature of the problem. One of these ways is the clinical interview, which is a goal oriented interaction between the clinician and the patient. This interaction provides the opportunity of getting information that will be helpful in the clinical decision making process. The interviews can be unstructured, semi-structured, or structured (Edelbrock and Costello 1988). Clinical interviews can be very helpful in getting background information and providing contextual information to help determine the severity, duration and intensity and pervasiveness of the child's problems. With the purpose of assisting clinicians in following DSM criteria during interviews, structured and semi-structured interviews developed:

- Semi-structured interview: Anxiety Disorders Interview Schedule for DSM-IV: Child and Parent Versions (ADIS for DSM-IV; Silverman and Albano 1996).

- Semi-structured interview: Schedule for Affective Disorders and Schizophrenia for School Age Children (K-SADS; Ambrosini 2000).
- Structured interview: National Institute of Mental Health (NIMH) Diagnostic Interview Schedule for Children (DISC), Version IV (NIMH DISC-IV; Shaffer et al. 2000).

Benefits of following such techniques are standardization of interview process, standard documentation of disorders, knowledge accumulation about disorders, increased reliability and repeatability of diagnosing process, more emphasize on empirically based treatments et cetera (Holmbeck et al. 2004; Ollendick and King 2004). The main drawback of these structured and semi-structured interview is that categorical approaches' discrete and mutually exclusive boundaries does not fit the reality of psychiatry patients. The patients might often have high level of comorbidity of disorders or special case that do not comply with their category defined by DSM criteria. In child and adolescent psychiatry, another shortcoming of DSM approach is that it does not take into account symptoms that change with age (Wenar and Kerig 2000)

Complementary to the interviews, norm based assessment and psychometric tests aim to answer questions related to how much a given behavior deviates from the norm. The focus is on evaluating the seriousness of the problem. Psychometric tools are available to determine a given child's functioning relative to the child's peers in various areas: intellectual functioning, neurological functioning, behavior, emotional status, personality and social functioning. Psychometric tests may be handled in the form of rating scales or paper-and-pencil tests, and they may be directed to a group. Many criticisms rose from weaknesses in psychometric measures, such as cultural bias and the role of environmental stimulation on performance outcomes. Doubts focus that the snapshot quality of a test result showing at best a point within a definable range, rather than a dynamic ongoing process.

Major Depressive Disorder:

Major depressive disorder (MDD) is "a mental illness characterized by a pervasive and persistent low mood that is accompanied by low self-esteem and by a loss of interest or pleasure in normally enjoyable activities" (DSM-5; APA 2013). MDD influences negatively the patient's family, work or school life, sleeping and eating habits and general health. Barlow and Durand (2005) reports that 3.4% of people with MDD committed suicide, and up to 60% of suicides were committed by people with depression or another mood disorder.

A diagnosis of MDD necessitates either a depressed situation, evident in anhedonia in adults or irritability in children or loss of pleasure in daily activities (DSM-5; APA 2013). There are also some potential symptoms in children: Failure to make expected weight gains, insomnia or hypersomnia, psychomotor retardation, fatigue, feelings of worthlessness, inability to concentrate and repeated suicide intention. The feeling is continuous and the symptoms are intense with some symptoms often occur on a daily level. Approximately 5% of the general population of children and adolescents will suffer depression. However, Costello and colleagues (2002) realized that the occurrence rate doubles from 2% in childhood to 4-7% in adolescence. They explained that adolescents have higher incidence of the melancholic type of depression. In parallel, Ryan and colleagues (1987) reported higher rate of the melancholic subtype of depression and self harming activities in adolescents than in pre-pubertal children. They also claimed that adolescent depression can convert to adult depression and there exist a stronger evidence of a genetic component in adolescent depression similar to adult depression. While boys and girls are equally likely to have depression at younger ages, depression is almost twice as common in adolescent females than males (Fleming and Offord 1990; Hankin and Abramson 2001).

Bipolar Disorder:

Bipolar disorder (BD) is “a mental illness with periods of depression and periods of elevated mood” (DSM-5; APA 2013). The elevated mood is known as mania. During mania mood the patient acts too energetic, happy or irritable. Patients with bipolar disorder do not consider the consequences of their decisions during mania mood. The sleeping need reduces usually during mania phases (DSM-5; APA 2013). On the contrary, patients show opposite behaviors such as crying, a negative view on life, and poor eye contact with people in the mood of depression. Family history and genetic factors have strong effects on having bipolar disorder. Anxiety disorders and substance use disorder are commonly associated with bipolar disorder.

Adolescent diffusion of bipolar disorder is estimated around 1% of the population, although there are difficulties in finding accurate occurrence rates for bipolar disorders. One of these difficulties is that the disorder shares symptoms of other common child and adolescent disorders such as attention deficit and hyperactivity disorder, or obsessive compulsive disorder. Bipolar disorder can be misinterpreted with attention deficit and hyperactivity disorder and conduct disorder because of overlapping symptoms. For children or adolescents who seem depressed and also demonstrate symptoms that is similar those of attention deficit and hyperactivity disorder but are more severe such as rapid mood swings, the symptoms should be evaluated for the existence of BD, especially if family history is positive for the disorder (NIMH 2000). According to Geller (2001), the biggest problem in the diagnosis of BD in children is how to differentiate a child with mania from a child with attention deficit and hyperactivity disorder.

Psychotic Disorder:

Psychotic disorder is a mental illness with abnormal condition of the mind as involving a loss of contact with reality. People in psychosis can demonstrate some personality changes and thought disorder. Related to its severity, this may be accompanied by unusual behavior, as well as difficulty with social interaction and problems in carrying out daily life activities.

Psychosis is a diagnosis of exclusion, not considered a symptom of a psychiatric illness until other relevant and known causes of psychosis are completely excluded (Freudenreich et al. 2012). Medical and biological laboratory tests should exclude central nervous system diseases and injuries, diseases and injuries of other organs, psychoactive substances, and toxins as causes of symptoms of psychosis before any psychiatric illness can be diagnosed (Freudenreich et al. 2012). People with psychosis have some of the following problems: hallucinations, delusions, catatonia, or a thought disorder. Social cognition problems also may occur.

Panic Disorder:

Panic disorder(PD) is a mental illness explained by recurring panic attacks, generating severe and intense episode of anxiety during panic attacks. These attacks generally last about ten minutes, can vary from five to twenty minutes even sometimes more than an hour, or until helpful intervention is made (DSM-IV; APA 2000).

According to the American Academy of Child & Adolescent Psychiatry, “panic disorder usually begins during adolescence and can be hereditary”.

General symptoms of a panic attack involve rapid heartbeat, perspiration, dizziness, dyspnea, trembling, uncontrollable fear such as: the fear of losing control and going crazy, the fear of dying and hyperventilation. Also some other symptoms are sweating, a sensation of choking, paralysis, chest pain, nausea, numbness or tingling, chills or hot flashes, faintness, crying and some sense of altered reality.

Separation Anxiety Disorder:

Separation anxiety disorder (SAD) is a mental problem in which a person feels excessive anxiety regarding big changes such as separation from home or from emotionally strongly bonded people. According to the American Psychology Association, SAD is “an excessive display of fear and distress when faced with situations of separation from the home or from a specific attachment figure” (DSM-5; APA 2013).

According to DSM 5 (APA 2013) one must display at least 3 of the following criteria to be diagnosed with SAD:

- Recurrent excessive distress when anticipating or experiencing separation from home or from major attached figures
- Persistent and excessive worry about losing major attachment figures or about possible harm to them, such as illness, injury, disasters, or death
- Persistent and excessive worry about experiencing an unfavorable event that causes separation from a major attached figure
- Persistent reluctance to go out, away from home, to school, to work, or elsewhere because of fear of separation

- Persistent and excessive fear of or reluctance about being alone or without major attachment figures at home or in other settings
- Persistent reluctance or refusal to sleep away from home or to go to sleep without being near a major attached figure
- Repeated nightmares involving the theme of separation
- Repeated complaints of physical symptoms such as headaches, stomachaches, nausea when separation from major attached figures occurs

Social Phobia:

Social phobia, is a mental problem, described by big amount of fear in some social situations, creates considerable distress and damages abilities to function in some parts of daily life (British Psychological Society 2013). It is the most common anxiety disorder and one of the most common mental illness. For example, 12% of American adults experienced social phobia. Phobias are controlled by escape and avoidance behaviors.

According to DSM-5 (APA 2013), the main indicators are “fear of being the focus of attention”, “treating in a way that will be embarrassing or humiliating”, avoidance and anxiety symptoms. Social phobia’s symptoms often go along with anxiety disorder, including excessive blushing, excess sweating, trembling, palpitations and nausea. Panic attacks can happen under pressure and uncomfortable situations. People with social phobia try for treating self medicate, especially if they are undiagnosed, untreated, or both; this can lead to alcoholism, eating disorders or other kinds of substance abuse.

Generalized Anxiety Disorder:

Generalized anxiety disorder (GAD) is a mental illness described with excessive, not controllable and groundless worry, that is, apprehensive expectation about events or activities (DSM-5; APA 2013). The excessive worry generally intervenes in daily life activities, as people with GAD typically anticipate disaster, and are overly concerned about everyday matters such as health issues, money, death, family problems, friendship problems, interpersonal relationship problems, or work difficulties (Torpy et al. 2011).

People with GAD may have physical symptoms such as fatigue, fidgeting, headaches, muscle tension, muscle aches, difficulty swallowing, stomach pain, vomiting, diarrhea, bouts of breathing difficulty, difficulty concentrating, trembling, twitching, irritability, agitation, sweating, restlessness, insomnia and inability to fully control the anxiety. These symptoms must be consistent and ongoing, persisting at least six months, for a formal diagnosis of GAD (DSM-5; APA 2013).

Agoraphobia:

Agoraphobia is a mental illness related anxiety in its own right where the patient perceives the environment to be dangerous, uncomfortable, or unsafe (DSM-5; APA 2013). For instance, these situations can involve common use areas, uncontrollable social situations, unfamiliar places. Agoraphobia comes from Greek language as "fear of the marketplace". In the DSM-5 (APA2013), agoraphobia is classified as being separate from panic disorder.

Agoraphobia is often confused with a fear of social embarrassment, as the agoraphobic fears the onset of a panic attack and appearing unconscious in public. Agoraphobia in childhood can be related with negative experiences such as the loss of a parent through separation or other stressful situations kidnapping, mugging (DSM-5; APA 2013).

Obsessive Compulsive Disorder:

Obsessive compulsive disorder (OCD) is a mental illness in which people feel the need to check things repetitively, make some routines again and again. These are called "rituals" that have the same thoughts repeatedly. People with OCD can not control either their thoughts or activities. These activities are usual activities such as hand washing and checking the door is locked. These activities can occur to a degree that the individual's daily life is negatively affected (NIMH 2000). Often they take up more than an hour a day (DSM-5; APA 2013). Most adults realize that the behaviors do not make sense (NIMH 2000). The condition is associated with tics, anxiety disorder, and an increased risk of suicide.

Enuresis & Encopresis:

Enuresis is an illness that is a repeated inability to control urination. Individuals are old enough to be expected to have such control. Involuntary urination is also known as urinary incontinence (Werry and Cohrssen 1965). Incontinence is an anxiety causing situation. Strong bladder contractions can cause leakage and results embarrassment, anxiety that lead to wetting bed at night.

Encopresis is an illness described as “voluntary or involuntary fecal soiling in children who have already been toilet trained” (Friman and Freeman 2010). People with encopresis generally leak stool into their underwear. The term is generally used for children. The symptom is used for adults as fecal leakage or fecal soiling. The psychiatric (DSM-IV; APA 2000) diagnostic criteria for encopresis are: Repeated passage of feces into inappropriate place such as underwear or floor whether intentionally or unintentionally. The DSM-IV (APA 2000) recognizes two subtypes: with constipation and overflow incontinence, and without constipation and overflow incontinence. In the subtype with constipation, the feces are not formed properly and leakage is continuous, and this can happen in sleep hours. This form may be related with oppositional defiant disorder or conduct disorder or more likely due to chronic encopresis that has radically deformed the colon and anus (DSM-IV; APA 2000).

Anorexia Nervosa:

Anorexia nervosa is mental sickness that relates to the refusal to maintain a minimally acceptable weight. People with this disorder will have their weight approximately 15% below normal levels based on the Metropolitan Life Insurance tables or pediatric growth chart. The DSM-5 proposes that a body mass index equal to or lower than 17.5 kg/m2 (APA 2013). Anorexics' the biggest fear of gaining weight is the critical point of their motivation to control their food intake to the extent that the disorder can be fatal.

Symptoms are refusal to have a normal body mass index, causes menses to stop, hair becomes brittle, and skin becomes yellow and unhealthy, fear of even the slightest weight gain, taking all prevention measures to avoid weight gain or being overweight, obsession with calories and fat content of food. (Nolen-Hoeksema and Hilt 2013).

Bulimia Nervosa:

Bulimia nervosa, is a mental problem related to eating behavior "characterized by binge eating followed by purging". Binge eating means that consuming a large amount of food in a short period of time. Purging defines the attempts to get rid of the food consumed. This may be performed by vomiting (Shepphird 2009). Most people with bulimia are at a normal weight (Attia 2010). Bulimia is often related with other mental disorders such as depression, anxiety, and problems with drugs or alcohol (Shepphird 2009). There is also a “higher risk of self harm and suicide” (DSM-5; APA 2013).

Symptoms may show if someone has bulimia nervosa: concern on number of calories consumed, extreme consciousness of weight, low self-esteem, low blood pressure, depression, frequent occurrences involving consumption of excessive portions of food (Marzola et al. 2013). Like many other psychiatric illnesses, delusions can occur. People with bulimia nervosa may also exercise to a point that excludes other activities (Robinson et al. 2006).

Attention deficit and hyperactivity disorder:

Attention deficit and hyperactivity (ADHD) is a mental illness defined by problems with paying attention, excessive activity, or difficulty controlling behavior which is not appropriate for a person's age (NIMH 2016). These symptoms begin by age six to twelve, are present for more than six months, and cause problems in school life (Dulcan and Lake 2012). In children, problems paying attention may result in poor school performance (NIMH 2016). Although it causes problems in modern society, many children with ADHD have a good attention span for tasks they find interesting (Dulcan and Lake 2012).

Although it is the most studied and diagnosed psychiatric disorder in children and adolescents, the cause is unknown in the most of cases (NIMH 2016). According to the World Health Organization that ADHD affected about 39 million people as of 2013. It affects about 5–7% of children when diagnosed via the DSM-IV (APA 2000) criteria and

1–2% when diagnosed via the ICD-10 criteria. ADHD is diagnosed approximately three times more in boys than in girls (Emond et al. 2009). About 30–50% of individuals diagnosed in childhood continue to have symptoms in adult life and among 2–5% of adults have the condition (Balint et al. 2009). The condition can be difficult to tell apart from other disorders as well as to distinguish from high levels of activity that are still within the normal-range (Dulcan and Lake 2012).

According to the DSM-5, symptoms must be present for six months or more to a degree that is much greater than others of the same age and they must cause significant problems functioning in at least two settings such as social, school/work, or home. The full criteria must have been met prior to age 12 in order to receive a diagnosis of ADHD (DSM-5; APA 2013).

An individual with ADHD can have most or all of following symptoms: Being easily distracted, missing details, forgetting things and frequently switching from one activity to another; having difficulty in holding focus on one task; being bored from a task after a few minutes, unless doing something enjoyable having difficulty focusing attention on organizing and completing a task or learning something new; having trouble with completing homework assignments, becoming easily confused, moving slowly, having a difficulty processing information as quickly and accurately as others, struggling to follow instructions (DSM-5; APA 2013).

Oppositional Defiant Disorder:

Oppositional defiant disorder (ODD) is a mental disorder that is defined as "a pattern of angry/irritable mood, argumentative/defiant behavior, or vindictiveness lasting at least six months" (DSM-5; APA 2013). Children with oppositional defiant disorder are not aggressive towards others. They do not harm or steal property (Nolen-Hoeksema and Hilt 2013).

The APA (2013) defines key diagnosis criteria of ODD as the followings: Angry/irritable mood, argumentative/defiant behavior, or long term grievance as evidenced by at least four symptoms from any of the following categories and showed during interaction with someone who is not a sibling.

Angry/Irritable Mood: 1. Hot tempered. 2. Is often touchy or easily annoyed. 3. Is often angry and resentful.

Argumentative/Defiant Behavior: 4. Problems with authority figures or for children and adolescents with adults. 5. Often actively refuses to comply with requests from authority figures or with rules. 6. often annoys others. 7. Often blames others for his or her mistakes or misbehavior.

Vindictiveness: 8. Has been vindictive at least twice within the past 6 months (DSM-5; APA 2013).

Conduct Disorder:

Conduct disorder (CD) is a mental illness diagnosed in childhood and/or adolescence. CD introduces itself through a repetitive and persistent pattern of behavior in which the basic rights of others or major age-appropriate norms are violated. These behaviors are often described to as "antisocial behaviors" (Hinshaw 2003). CD is often interpreted as the pioneer of the antisocial personality disorder, which is not diagnosed until the person is 18 years old (DSM-5; APA 2013).

One of the factors of conduct disorder is a lower level of fear. If a child does not learn how to handle fear or distress the child will be more likely to act impulsively to other children. If the educator provides alterative intervention and teaching children better empathy skills, the child will have a lower level of conduct disorder (Spinrad and Stifter 2006).

Tic Disorder:

Tic disorders is defined by DSM-IV based on type of motor or phonic neurons and duration of tics such as sudden, rapid, non-rhythmic movements (DSM-IV; APA 2000). The fifth edition of the DSM (APA 2013) classifies Tourette's syndrome and tic disorders as motor disorders listed in the neurodevelopmental disorder.

Post-Traumatic Stress Disorder:

Post-traumatic stress disorder (PTSD) is "a mental illness that can occur after an individual is exposed to a traumatic situation, such as sexual assault, warfare, traffic collisions, or other threats on a person's life" (DSM-5; APA 2013).

Symptoms of PTSD are disturbing thoughts, feelings, or dreams related to the events, mental or physical distress related to a trauma, attempts to avoid trauma related issues, changes in the person's thoughts and feelings. These symptoms can last for more than a month after the traumatic event. Young children are less possible to show distress but instead may express their memories through play (DSM-5; APA 2013). PTSD increases the risk of suicide (Hoskin et al. 2015).

In the United States about 3.5% of adults have PTSD in a given year, and 9% of people develop it at some point in their life. In much of the rest of the world, rates during a given year are between 0.5% and 1% (DSM-IV; APA 2000). Higher rates may occur in regions of armed conflict (Hoskin et al. 2015). It is more common in women than men.

2.4-Use of Social Networks Data in Adolescent Psychiatry

Wide spread use of SNSs generates huge amount of data about people who use them. The content of the data is obviously related to the habits and behaviors of SNS users. To understand the potentials of SNSs data in adolescent psychiatry, adolescents' unique behaviors on SNSs must be investigated. In the literature, there are numerous studies that examine the behaviors of adolescents on SNSs.

Christofides and colleagues (2011) conducted a comparison study between adolescents and adults in terms of information share on Facebook and use of privacy control settings of Facebook. Adolescents shared more information and used less privacy control settings compared to adults. While adolescents spent more time on Facebook, adults had more self esteem on Facebook. Supporting these finding, Denti and colleagues (2012) conducted a survey study on Swedish population. They also found adolescents spent more time on Facebook and disclose more information than adults. Adolescents also give more importance to their popularity on Facebook than adults.

Another aspect of behaviors of adolescents on SNSs examined in the literature is that whether adolescents disclose information in a rational and intended way or an impulsive and unconscious way. In the study of Gool and colleagues (2015), it has been reported that although most adolescents disclose information with a rational decision, a significant portion of information share is done with an impulsive decision. This shows the importance of educating adolescents about the risks and benefits of SNSs.

Adolescents seek support on SNSs proportional to their exposed stress level. When they feel support from their network on SNSs, their stress level and depressed mood decreases. This mechanism is similar to the one in traditional social support seeking context (Frison and Eggermont 2015).

Singleton and colleagues (2016) explored the use SNSs by adolescents accessing mental health services and the effect of SNSs on their mental health. Their study focused on adolescents' perceptions on interactions via SNSs and their wellbeing and distress. They worked with 12 participants from England, participants' ages were between 13 and 18 years old. The clinicians made semi-structured qualitative interviews with 12 participants. They collected data in three interviews for each participant. They found that adolescents feel SNSs are unavoidable because of the fear of missing updates in their social environment. Adolescents use SNSs intensively, and they perceive some positive and negative sides of SNSs. Threats and judgment are the main negatives related to using SNSs. On the contrary, connection and support are the main positives of using SNSs for adolescents.

Social comparisons are central to young people's development of identity. By observing other people in society, they foster their understanding of themselves as being able to develop the skills to succeed in a way that is valued by society (Erikson 1968). Threats and judgment coming from SNSs are dangerous to the development process of adolescents' identity. These negative sides of SNSs affected young people's mood, self esteem; increased their feelings of anxiety, insecurity and low mood, which could be associated with coping behaviors such as self-harm. The study also revealed that the social comparison via SNSs profile looking and checking peers was mostly done upward which means that comparing oneself with better people. This may have a significant impact on self-esteem (Krayer et al. 2008). Such findings may contribute to explaining the links found between SNS use and low self-esteem (Błachnio et al. 2016). Moreover, Chen and Lee (2013) claimed that increased Facebook use is correlated with greater distress and reduced self esteem.

On the other hand, Singleton and colleagues (2016) pointed out that SNSs also had positive sides that “validated and normalized emotional experiences and helped young people to feel included, worthwhile and better equipped to manage their distress”. In the study, adolescents had an ideal profile for themselves to be presented on SNSs, rather than having a profile that is open and honest reflection of themselves. This ideal profile depends on their value mechanisms. They behaved carefully to “fit in” the ideal profile that they perceived as valuable by their online network. They created these ideal by maintaining and incorporating the features of the ideal profile which receive validation from others (Schlenker 1986). Balick (2014) suggests that SNS identities are not “virtual” but representations of people’s multiple images corresponding to the imaginary and real SNS audiences, allowing young people a forum for “identity-testing”. In Singleton’s (2015) study, adolescents had different SNS accounts and these accounts were tried and tested with different audiences. For different situations, they created concepts. For instance, they were seeking emotional support through a more honest and direct but anonymous version of themselves, while maintaining relationships with friends and family through a carefully portrayed public version of themselves. This anonymity provided a chance to the young people to move freely in the difficult situations such as described as adolescents' online support seeking times. This was minimized by an increased impression management (Oh and LaRose 2016).

Some scholars believe that SNSs can cause to a dangerous addiction which has similar traits with drug addiction. They study the effects of SNSs addiction, its incidence in society, and remedies to fight against this addiction (Rasool et al. 2015; Kirik et al. 2015). With purpose of measuring SNSs addiction, Eijnden and colleagues (2016) presented the social media disorder scale and conducted its validity and reliability tests.

After examining unique SNSs usage habits and behaviors of adolescents, personality characteristics of individuals is critical for further understanding. Although some scholars claimed that adolescents reflected an idealized-self on SNSs, Back and colleagues (2009) reported Facebook profiles reflected actual personality. Regardless whether SNSs reflect actual or idealized personality, the strong relation between personality characteristics and SNSs usage habits and behaviors of adolescents is inevitable (Ong et al. 2010; Ross et al. 2009; Amichai-Hamburger and Vinitzky 2010; Zhong et al. 2011; Ryan and Xenos 2011; Wang et al. 2012). The studies suggested that extraverts use communicative functions, agreeable and self confident people comment on other people's shares, open and sensation seeking people play online games, and narcissistic people share their attractive photos.

In today's connected world through internet, technology use in psychiatry is becoming critical and expected to be more developed in the future. SNSs use in psychiatry can bring opportunities such as informing adolescents through better communication with them on SNSs (White and Dorman 2001). From the analysis of SNSs data, surveillance of adolescents can be conducted in terms of their mental and emotional well being. Choudhury and colleagues (2013) advocated that more detailed measurement of depression symptoms is possible due to fast expansion of SNSs. The social network sharing of diagnosed patients can be beneficial to identify the relation between depression and personal posts by examining with several mathematical models. They analyzed Twitter shares of a group of people who have clinical depression diagnosis. The analysis used a probabilistic model to see the indicators of depression in posts. They created a social media depression index to measure the levels of depression in public. They tested the several factors of depression in population by early psychiatric findings and find a high correlation with historical data (Choudhury et al. 2013).

The diagnosis of mental problems is based on the communication between doctors and patients. In the communication process, the diagnosis is based on messages sent by patient and received by psychiatrist. Patients can also send these messages to all the relevant people around them via several functions on social network sites. There are academic studies that are based on linguistic data search on social network sites. Bantum and Owen (2009) focused on their study on improving internet based intervention methodologies for women with breast cancer. Their method works with patients' emotional expressions on their posting and shared contents. This was analyzed via rater coding and computerized coding methods: Linguistic Inquiry and Word Count (LIWC) and Psychiatric Content Analysis and Diagnosis (PCAD). They found better correlation with the LIWC, which is also faster in identification of emotional texts of patients' content than PCAD. There are recent improvements in computerized content analysis programs. Therefore, accuracy of internet and computer based tools could go beyond the limitations of human capacity on identification of possible interventions in the future.

Gürbüz (2015) made a research study about social network sites use of adolescents with major depressive disorder and analyzing their self expression on SNSs.

This study also aimed to evaluate the several anxiety disorders and other mental problems among depressive adolescents. This study was done with 53 participants and they were patients of a psychiatry clinic in Istanbul, Turkey. Also they worked with a non-depressed 55 adolescents as a comparison group to identify differences. During their study social anxiety and social media questionnaires were used to get information from adolescents. The results of the study were showing that anxiety scores were average in both participant types, the spent time was higher among depressed adolescents than non depressed ones. Also, depressed adolescents expressed several negative emotions and disclosures such as worthlessness, loss of concentration and thoughts of suicides. The study showed that depressed young people express themselves on social networks more than their non depressed peers. Therefore, the posts of young people on social network sites could be useful and a guide for their relatives, friends and for psychiatrist. But, in Gürbüz's study, sample size was very limited to present the further possible relations of depression intensity level with social media usage. Larger participant population is required to support its findings. The findings are also supported by the study of Park and colleagues (2013) who developed a web application to identify depressive symptoms and support depressed people. While they found the more depressed people are, the more they use Facebook; they also read more tips and facts about depression.

Overall, the possibility of detecting psychiatric symptoms from adolescents' SNS profiles was confirmed by a number of scholars and their studies (Lin et al. 2014; Liu et al. 2015; Sinn and Syn 2013; Settanni and Marengo 2015). To make this possibility a practical reality, technical developments are necessary. Coppersmith and colleagues (2014) admitted the issue and contributed to the progress by a novel method for gathering

SNSs data and analyzing it specifically related to post traumatic stress disorder, depression, bipolar disorder, and seasonal affective disorder. There are other developments regarding technical aspect of the topic (Howes et al. 2014; Ji et al. 2015; Homan et al. 2014).

2.5-Literature Gaps and Opportunities

One of the valuable use of SNSs in adolescent psychiatry was public surveillance of mental health status. The studies aimed at public surveillance of mental health used often one source of data such as twitter data in the study of Choudhury and colleagues. This generates a potential method bias because the sample is drawn from twitter users. This issue might be partially tackled by adding complementary data sources such as Facebook or other SNSs usages, web browsing logs, health records, and demographics. There are also privacy concerns regarding the use of SNSs data, and legal developments are necessary to address these concerns.

Another important usage possibility of SNSs is to improve the communication with adolescents regarding their mental health issues. Critique of such use of SNSs is often related to the management process of the communication. Healthcare professionals usually does not possess the competences to manage SNSs communication, so people skilled at professional use of SNSs must be employed by healthcare organizations for such communication to be effective. On the other hand, SNSs are open to misinformation generated by unreliable sources. Adolescents often lack skills necessary to differentiate such sources and protect themselves from misinformation (Fernandez-Luque and Bau 2015).

Detecting psychiatric symptoms using SNSs data was studied by numerous scholars who showed the feasibility of the idea with current technologies. However, all the studies, to the best of our knowledge, are conducted using a limited sample size as a prototype application. Therefore, the idea is not in practical use by clinicians. Considering SNSs usage differences across cultures around the world, it is not known whether the idea would work universally. Validity and reliability studies of the idea using larger samples must be conducted to have a better idea of applicability of the idea.

In this study, we focused on the idea of detecting psychiatric symptoms using SNSs data, mainly due to great value generation potential of the idea when practically used in clinics. We also chose to be focused on adolescents because of their unique usage habits and behaviors that work better for detecting symptoms.

3-Objectives and Research Framework

3.1-Objective

As explained in the chapter of 'Use of Social Networks Data in Adolescent Psychiatry', it is possible to detect psychiatric symptoms of an adolescent using her or his data on social networking sites. The idea does not aim to replace psychiatrists with a computer algorithm. Instead, its goal is to support psychiatrists in their diagnoses phase with additional valuable data. Although there are many academic studies and trial applications of this idea, currently there is not a practical standard use of the idea in healthcare systems. Moreover, the results of such pioneer works are neither conclusive nor complete in terms of validity or universal applicability. Therefore, there is not a consensus about whether detecting psychiatric symptoms using SNSs data is possible all around the world in a reliable manner.

The objective of this study is to investigate the possibility of detecting child psychiatry symptoms from SNSs data. Considering the existence of advanced social network mining techniques, we assume that the symptoms can be detected as long as adolescents share their symptoms. In other words, current state of technology is capable of analyzing social media content of a person and detecting psychiatry symptoms if shared. This reduces our investigation to whether adolescents share their symptoms on SNSs. With this purpose, a survey has been conducted for adolescents admitted to a child and adolescent psychiatry outpatient clinic in Turkey. The main goal of the survey is to understand under which conditions and how frequent patients share their symptoms on their SNSs profiles.

The survey was prepared and conducted with the collaboration of Uludag University, School of Medicine, Department of Child and Adolescent Psychiatry, Bursa-Turkey. The collaborating team developed the hypothesis based on theory and previous research. From the hypothesis, the conceptual framework was drawn. The survey questionnaire was prepared based on the hypothesis and the conceptual framework. Survey application, recording the results, and potential analysis were discussed and decided in collaboration. The processes will be explained in details in the following chapters.

3.2-Hypothesis

All the main players of social media platforms try to increase their user engagement levels. People respond to SNSs’ strategies according to their personal preferences and networks on these platforms. Child and adolescent psychiatry patients engage social media sites in different levels of engagement depending on their disease and the level of their disease. In her study with depressive patients, Gurbuz (2015) found that depressive patients spend more time on social media platforms than the control group. Considering feeling worthless, guilty, lack of pleasure, lack of concentration, anger and suicidal thoughts as depressive symptoms, depressive patients also share depressive symptoms more frequently than the control group. Supporting these findings, Lin and colleagues (2014) found the more the size and density of user's network on SNSs are, the more emotional disclosure users do. They also associate density of the network with positive and negative emotion disclosure while the size of network is associated with only positive emotion disclosure.

While some people consider their social media use as a time killing activity, other might consider as an important part of their life. People might consider SNSs platforms as an important tool for their social life. Moreover, they might be able to share and find support on certain topics that they can not share in their daily life. In the literature, scholars claim that the value attributed to social media platforms increases emotional disclosure of people (Sinn and Syn 2013; Singleton at al. 2016; Denti at al 2012; Rosen et al. 2012; Frison and Eggermont 2014; Gool et al. 2014). Emotion disclosure and looking for help are important drivers of increased perceived value of SNSs for people. People who share their emotions and look for support on SNSs consider these websites as an important part of their life and they feel isolated in the absence of SNSs. The behavior of people's network on SNSs is also a determinant of the value attributed to SNSs by people. People tend to attribute more value to SNSs when they receive support from their networks on SNSs. If a person's networks disclose emotions and look for support on an SNS, the person is likely to do the same thing and feeling the support from his/her network. To sum up, the value attributed to online social platforms by individuals depends on personal, SNS's characteristics and the characteristic of the network in the SNS (Christofides et al. 2011; Sinn and Syn 2013; Rosen et al. 2012; Frison and Eggermont 2014). Perceived value of social network sites positively affects adolescent's share of symptoms on these sites.

H1: Perceived value of SNSs positively affects adolescent's share of symptoms on SNSs.

People disclose their emotions in their daily life because it stimulates social interactions and increase interpersonal intimacy (Derlega et al. 1987; Laurenceau et al. 1998; Rime 2009). The drivers behind disclosing positive emotions are to have longer hedonic feelings, to have somatic activity and amusement, to have life satisfaction and better relationships (Mauss et al. 2011; Gross and Levenson 1997; Gable and Reis 2010). On the other hand, the drivers of sharing negative feelings are to reduce the intensity of fear, traumatic stress, and depression; to relieve the stress of suppressed negative feelings (Langens and Schuler 2005; Greenberg and Stone 1992; Radcliffe et al. 2010; Pennebaker 1997). In both cases, people carefully choose who to share their feelings with. This mechanism is replicated in a quite similar way in SNSs (Lin et al. 2014; Valkenburg et al. 2005).

Edmondson (1999) defined psychological safety as shared beliefs in a social network that individuals feel safe to take interpersonal risks. Psychological safety goes beyond the feeling of trust in networks. In psychologically safe networks; people mutually respect each other, are comfortable expressing their differences, and have no worries about negative consequences as a result of their emotional disclosure. People share their feeling in such networks and do not expect to have any negative feedback or harm from the members or moderators of the network. Hence, people should be able to trust also the SNS companies for an SNS to be psychologically safe (Nembhard and Edmondson 2006; Walumbwa and Schaubroeck 2009).

As a result of the arguments in the literature, we expect perceived psychological safety to have direct and indirect effects on symptom share of adolescents. Therefore, the following hypothesis are adopted for our study.

H2: Perceived psychological safety by adolescents in SNSs positively affects their share of symptoms on SNSs.

H3: There is a positive moderating effect of perceived psychological safety on the relationship between perceived value and share of symptoms.

3.3-Conceptual Framework

The conceptual framework is represented in the figure below. The hypothesis developed above represented as arrows.

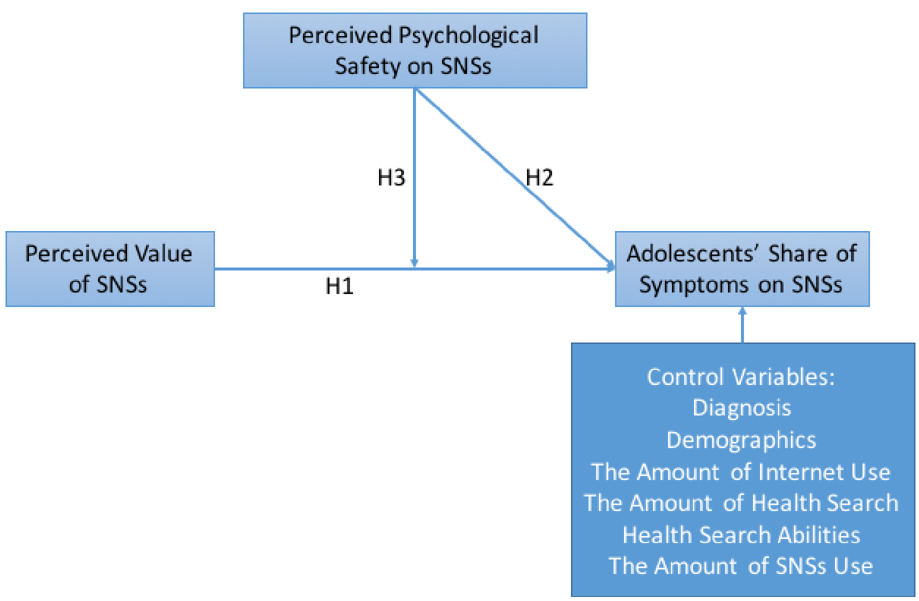

Figure 9: Conceptual Model

In this study, the symptoms were decided in collaboration with The Child and Adolescent Psychiatry Department based on a standard semi-structured interview technique called Kiddie-Sads-Present and Lifetime Version (K-SADS-PL). The technique was developed by Kaufman and colleagues (1997), and reliability and validity studies were conducted. Then, K-SADS-PL was translated to Turkish by Gökler and colleagues (2004) who also conducted reliability and validity studies on Turkish population. Since then, this interview technique is widely accepted by scholars and used by psychiatrists in the field of child and adolescent psychiatry in Turkey as well. The technique basically consists of guidelines for psychiatrists to be used while they are questioning the symptoms of potential patients. While K-SADS-PL questions all the possible symptoms, some of them are not appropriate for the current survey study. Therefore, all the symptom categories are examined and the following categories are selected for the survey: Depressive symptoms, anxiety, somatic complaints, self-harm symptoms, traumatic events, anger, regret related symptoms. As a combination of all the symptoms selected, overall symptom share of adolescents on SNSs was evaluated.

The control variables were determined from past studies related to emotional disclosure of adolescents. Diseases and demographics of adolescent patients might have effects on their symptom share on SNSs, so diseases and demographic variables will be controlled for (Gool et al. 2015; Sinn and Syn 2013; Settanni and Marengo 2015). The amount of internet use is expected to positively affect symptom share (Cline and Haynes 2001; Frost and Massagli 2008). The amount of health search and health related online search abilities are expected to be correlated with each other and also positively affect symptom share (Hargittai 2001; Skinner et al. 2003; Sarasohn-Kahn 2008; Nutbeam

2006; White and Dorman 2001; McMullan 2006). Finally, the amount of SNSs use will be controlled for and it is expected to positively affect symptom share (Christofides et al. 2011; Sinn and Syn 2013; Rosen et al. 2013; Frison and Eggermont 2014).

4-Methodology and Results

In this section of the report, the methodology followed to test our conceptual model built in the previous section will be explained in detail. All the steps in our methodology was designed and applied with close collaboration with The Psychiatry Department. Firstly, the design of the survey was done. Next, the survey was applied to the patients and results were entered to MS excel from paper forms. The data was checked and prepared for the analysis before starting explanatory analysis. After having meaningful results from explanatory analysis, conceptual model was tested and results are reported.

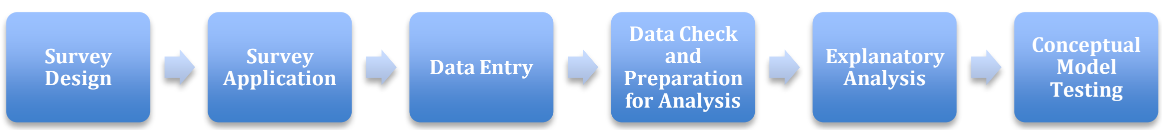

Figure 10: Steps of The Methodology

4.1-Survey Design

The survey was designed considering our main objective which is to evaluate the possibility of detecting child psychiatry symptoms from SNSs data. Therefore, it is necessary to understand clearly the relation of teenagers' social network sites usage habits with their mental health problems. With this goal and our conceptual model, the survey was designed to measure adolescents' symptoms share on SNSs.

Firstly, the target of the survey was decided as the potential patients who apply to the clinic and aged between 12-18. The minimum age limit was decided considering cognitive development level of children to understand our questionnaire, possibility of having an SNS account and accepted definition of adolescents in the literature. Although most SNSs, for example Facebook, does allow people under 13 to have an account, it is known that children under 13 are using Facebook by changing their birth year. The maximum age limit is the limit of child psychiatry clinic, meaning that people aged over 18 should apply adult psychiatry clinic. Although applying the same or a complementary survey to the parents was considered at the initial phase of the survey design, it was decided not to apply it because of the personal nature of sharing feeling on SNSs and the risk of affecting adolescents' answers. Adolescents might feel pressure to comply with their parents' answers when the parents are answering the same or complementary questions. Therefore, we applied our survey to adolescents without their parents seeing them.

The questions of the survey were designed considering the control variables and each block of the conceptual model. Before preparing the questions, the criteria for the questions were discussed. Besides standard survey questionnaire criteria, we had specific points related to our audience. The first one was to be clear and quickly fillable survey. Moreover, the questions should be exciting for potential patients to keep their attention on the questionnaire. Another point is that the attention should be kept alive with different question types. Monotone and same style questions might bore them and lead to meaningless results. We used reverse questions to measure their conscious level and to detect if they are speeding or cheating.

The first control variable was diseases in our conceptual model. There was no question to respondents of the survey related to their diseases. Instead, the disease of each respondent was indicated by the psychiatrists at the end of diagnosis process.

The standard demographic test of the clinic was applied at the beginning of each survey. This demographic test was designed over time with the experience of previous surveys and complying with Turkish laws regarding patient privacy and protection. This demographic test contained questions about patients' age, sex, parental marriage situation, house members, parents' education level and job situation, household income, number of siblings and physiological and psychological chronical diseases. These question are important to create connection between patients' environment and their SNS usage characteristics. These variables were used as control variables in our conceptual model.

For the question creation regarding the rest of control variables and each block in our conceptual model, a literature search was conducted and a pool of questions used in the literature was created (Ross et al. 2009; Zhong et al.2011;Kırık et al. 2015; Eijnden et al.2016; Gool et al. 2014; Sinn and Syn 2013; Rosen et al. 2012; Frison and Eggermont 2014).

The third control variable in the conceptual model is related to the amount of internet use. The questions for this variable was designed to understand which devices are preferred (e.g. computer, smart phone, and tablet) and how frequent they are used. Respondents had six choices corresponding to different level of frequencies of internet use starting from "more than 6 hours per day","4-5 hours per day","1-3 hours per day", "less than 1 hour per day", to "less than 5 hours per week".

The fourth control variable of the conceptual model is about the amount of health related search on the internet. For this variable, a table was created to make understanding easier for adolescents. The questions were whether the respondent searches online information in different phases of his/her journey to any clinic. The phases were presented in a logical order in the questionnaire. The first question was about healthcare system details such as working hours, contact information. The second question was about health related concerns and symptoms. The third one was about reviews for doctors. The fourth and fifth ones were about diagnosis, treatment and side effects of prescribed medicines. The final question was about people with similar conditions to learn about their experiences. The main goal is to question respondents whether they are searching about each of the topics mentioned. For each question, respondents were able to say “No, not interested”, ”No, but interested” or “Yes”. If they say yes, they had to select a frequency as “Rarely”, “Sometimes”, “Frequently”. After selecting frequency, they could also select the types of websites they generally use and how frequent they use that type of websites. The types of websites were given as official websites, online encyclopedias, blogs and forums, social media sites.

For measuring health search activities, content creation about health related topics is also considered as an important indicator of the mount of health search on the internet. It is expected to search more if the content creation of an individual is high. We determined blog, forums and social media websites as platforms for adolescents to possibly create content. Concerning each topic that was questioned in the previous question, the frequency of content creation related to each of the topics was asked in the form of table. Young adolescents might not know the meaning of content and they might think of more official contents. For this reason, an explanation for the meaning of content was provided as share of pictures, videos, writing your opinions or comments.

Considering the fifth control variable, the aim is to measure the health related online search abilities of adolescents. This part was designed in the form of 1-7 Likert scale, 1 representing "strongly disagree" and 7 representing "strongly agree". "N/A" option was also put for "not applicable". There were four questions which are about reaching information sources, distinguishing valuable information, comprehension, and decision making based on the information found.

For the last and sixth control variable of the conceptual model, the existence of SNS accounts and the amount of SNS use was questioned. The most popular SNSs in Turkey are listed and the respondents were to answer whether they have an account and how frequent they use that social media site. The list of sites in the order of popularity is the following: Facebook, Instagram, Twitter, Snapchat, Google+, Onediyo.com, Vine, Pinterest, Scorp, Tumblr, and Ask.fm.

Regarding the first construct of the conceptual model, attributed value to SNSs were measured. Considering different aspects of attributed value explained in hypothesis part of the report, the questions were created. Looking for psychological help, feeling more social with SNSs, considering SNSs as an important part of life, sharing feelings and receiving support were the main topics of the question. In total four questions were asked in this part.

The second construct of the conceptual model was related to perceived psychological safety on SNSs. Regarding different aspects of psychological safety explained in the hypothesis part, four questions were asked for this construct. The questions were about feeling more relaxed, expressing oneself better on SNSs, share feelings honestly and openly, having supportive friends, and emotion disclosure of friends on SNSs. The questions of the first and second constructs of the conceptual model designed in 1-7 Likert form, again 1 representing “strongly disagree” and 7 representing “strongly agree”. “N/A” option was also put for “not applicable”.

The final and third construct of the conceptual model is about psychological symptom share of adolescents on SNSs. For this part, 20 questions, each question representing a symptom, were prepared. For each question, the respondents were asked whether they do the SNS activities, which are chatting with friends, updating profile status, changing profile picture, sharing a picture, video, or a song, and commenting on friends’ shares. The frequency of doing these activities were also asked. The questions corresponding to symptoms were selected from K-SADS-PL technique. The selected symptoms fall into seven categories which can be seen in table below. After preparing the questions for each category, we put them into a randomized order.

Table 3: Categories of The Selected Symptoms for The Questionnaire

Symptoms	Feelings/Situation
1-Depressive Mood:	Feeling bad, happy, betrayed; Having high self confidence; Feeling people like me; Others treat me poorly; Feeling everything will be bad
2-Anxiety:	Feeling peaceful and comfortable, nervous, anxious, scared; Having homework or an assignment to finish; Feeling something bad will happen
3-Somatic Complaint:	Having a headache, stomachache or nausea; concerns about his/her health
4-Suicidial Symptoms / Self Harm:	Thinking about self harming
5-Traumatic Events:	Going through a traumatic event; Having headache, stomachache or nausea; Something really good happens to me
6-Anger:	Feeling angry
7-Regret:	Treating other people badly

The language and the word choice of the questions were simple and easy for adolescents to understand the questions. Some of the questions were presented in a table form, so that the effort to understand each question was reduced. During the questionnaire preparation phase, pre-tests were conducted to several adolescents. According to the feedbacks from pre-tests, the questionnaire was modified and final questionnaire was obtained. During the pre-tests, the time needed to fill a questionnaire by an adolescent was approximately 20 minutes, which was confirmed by actual application of the survey later on. Twenty minutes is a long time for a survey and prone to give meaningless results due to speeding and cheating. However, we addressed this issue in our survey application phase by reviewing their questionnaire after filling.

4.2-Survey Application

The survey was applied at the outpatient clinic of The Child and Adolescent Psychiatry Department to the patients who are aged between 12 and 18. When they arrived the clinic for their appointments, the clinic personnel firstly introduced our study, its purposes and explained the value of their contribution. Moreover, non-commercial goals of the study and the absence of conflicting interests were explained to patients and their parents. According to Turkish regulations regarding patients' privacy and protection, the patients and their parents were asked for their consent. They were able to opt out of the study any time if they change their mind. However, after they were agreed to contribute and gave the consent, they were asked to fill the questionnaire properly and they said their doctor will check the questionnaire with them in the doctor's office. The volunteered patients filled the questionnaire while they were waiting for their appointment with the doctor. They were also guided to sit away from their parents in order to eliminate the effect of parents on survey results. Although the parents knew what the survey was about in general, the patients knew that their parents do not know each question and their answer to them.

After completing the questionnaire, the patients went to the doctor's room, and the psychiatrist reviewed the questionnaire with the purpose of fixing missing parts and conflicting answers. Next, the psychiatrist started applying the K-SADS-PL technique with the patient and continued to an other interview with one of the parents, which is the next part of K-SADS-PL. At the end of these interviews, the psychiatrists determined and wrote the patient's diagnosis, the length of disease, the treatment, and the length of treatment after the patient and the parents left the room.

This procedure was applied for 6 weeks between the dates of 25th of May 2016 and 10th of July 2016. For each patient, introducing the study and asking consent took around 10 minutes. Questionnaire filling for patients took 20 minutes on average. The review by the psychiatrists took between 2 to 20 minutes depending on the amounts of missing parts and conflicting answers.

4.3-Data Entry

At the end of survey application process, a total of 273 survey results were collected in paper form. For further analysis, these results had to be transferred to a digital format. An MS Excel sheet is created with certain rules defined before entering the data so that any mistake during data entry was eliminated. All the answers in the questionnaires were coded to numbers so that the statistical analysis software can work. Entering each survey result from paper form to the Excel sheet took 10-12 minutes. During the process, the questionnaires with excessive missing data were identified to be excluded from our analysis. In total, 21 survey results were identified as having excessive missing parts. On the other hand, complementary and reverse questions were examined during the data entry process. A total of 28 survey results failed to pass this examination and considered as unconsciously filled questionnaires. Overall, 49 survey results were excluded from our analysis. There remained 224 survey results to be used in our analysis and testing the conceptual model. The comparison of excluded and included results in terms of our control variables will be presented in the explanatory analysis part of this report. Whether our sample of 224 patients represents child psychiatry patients in Turkey will also be reported in the same part of the report.

The process of data entry was conducted by the psychiatrists with the help of clinic personnel. Most patients wrote their name on the questionnaire paper, although it was not asked by the questionnaire and they were told not to write any personal identifier including their names on the questionnaires. We believe it is a strong habit from their school. Because most of the questionnaires included names, the psychiatrists and clinic personnel were the only people who can legally see the questionnaires according to Turkish laws regarding patient’s privacy and protection. Therefore, the data entry process was conducted by them.

4.4-Data Check and Preparation for Analysis

IBM SPSS version 23 was used for the analysis in this study. The raw data in the Excel sheet was imported to SPSS. Before starting the analysis, the possible effects of common method variance (CMV) was evaluated.

Common method variance (CMV) is defined as "systematic error variance shared among variables measured with and introduced as a function of the same method and/or source" (Richardson et al. 2009). Common method bias is a concept that is caused by the measurement method used, not by the network of causes and effects in the studied model. For instance, an electronic survey method could influence results for participants who could be unfamiliar with an electronic survey interface differently than for people who might be familiar. If measures are affected by common-method bias, the inter-correlations among them can be inflated or deflated depending upon several factors (Williams and Brown 1994). It is sometimes assumed that CMV affects all variables. Evidence shows that the correlation between two variables might be affected by CMV. CMV is a function of both the method and the particular constructs of the model being measured. Because CMVs can have possibly serious effects on research results, it is important to understand their causes and when they are especially likely to create a problem (Podsakoff et al. 2003). So that, we should identify the most probable roots of method bias and address them using ex ante and ex post remedies.

CMV has different types of roots and one of them is common scale format, which refers to artifactual correlated variation produced by the use of the same scale format, for instance Likert scales on a questionnaire. In our survey, different scale formats were used for different questions. For the same scale questions, reverse questions were asked. Another type is common scale anchors that refer to the repeated use of the same anchor points extremely, always, never on a questionnaire (Tourangeau et al. 2000). The survey results were examined for this type of bias in our study.

Another possible root of CMV is the implicit social desirability connected with answering questions in a questionnaire in a specific way, again causing the indicators to share a certain amount of common variation (Kock 2015). Social desirability is “the need for social approval and acceptance and the belief that it can be attained by means of culturally acceptable and appropriate behaviors" (Crowne and Marlowe 1964). It is observed as the tendency of individuals to present themselves in a favorable light, regardless of their true feelings about a topic. This tendency is problematic, not only because of its potential to bias the answers of respondents, but also because it may mask the true relationships between two or more variables. Social desirability could create fake relations, serve as an obstacle variable that hides the true relationship between variables, or serve as a moderator variable that influences the nature of the relationships between the variables (Ganster et al. 1983). The topic of this study is not considered susceptible to social desirability. Although there are also other types of biases in the literature, they are not considered as relevant for our study.

In the design phase of the survey, the language and word choice of the questions were carefully evaluated to prevent any ambiguity, vague, and unfamiliar terms with the purpose of addressing CMV. This was also examined with the pre-tests. Before the survey application, the clinic personnel clarified the confidentiality of respondents, non-existence of correct or incorrect answers, and importance of honest answers. In terms of ex post CMV remedies, Harman's single factor test was adopted.

Harman's Single Factor Test

Harman's single-factor test is a popular method among researchers to test common method variance. Procedurally, it is conducted by loading all the variables in a study into an explanatory factor analysis and checking the unrotated factor solution. It gives the number of factors that explains the variance in the variables of the study. It is interpreted as if there is a considerable common method variance then a single factor would account for the majority of variance in the variables.

On the other hand, confirmatory factor analysis (CFA) is also used frequently by researchers. Because using CFA is more robust so differences between the one-factor model versus the multi factor model can be tested via the chi-square difference test. Using only EFA allows researchers to provide an estimate based on the results, but no direct test of differences (Craighead et al. 2011). Unfortunately, conducting a CFA is not a very effective way of identifying common method bias. Models may pass criteria for acceptable convergent and discriminant validity, and still be contaminated by common method bias (Podsakoff et al. 2003).

The single factor test is actually not a perfect test for CMV. Because, for example, a single factor can emerge as a result of an EFA. Then one can not be sure that this factor contains method variance or measures a single characteristic. (Podsakoff et al. 2003).

In this study, Harman's single factor test was conducted on the key variables of the survey. The result revealed that the factor, which has the highest percentage in terms of explaining the variance in the variables, was accounted for 27.6% of the variance. This result indicates minimal evidence of CMV (Harman 1967).

4.5-Explanatory Analysis

In this part of the report, the result of each variable in our survey study is presented. Our explanatory analysis regarding each variable is explained and their results are presented.

Diseases (Diagnosis)

The first variable was the diagnosis of the patients. The most common disease among our sample patients was major depressive disorder with 103 diagnosed people. The other common diseases were attention deficit and hyperactivity disorder with 57 adolescents and generalized anxiety disorder with 29 adolescents. The results can be seen in the table below. There are 256 diagnoses in total and 32 people with two diagnoses, which gives 224 adolescents in total.

Table 4: Diagnosis of The Respondents

	Diagnosis	**Number of Patients**	**Percent**
1	Major Depressive Disorder	103	46,0%
2	Bipolar Affective Disorder	5	2,2%
3	Psychotic Disorder	1	0,4%
4	Panic Disorder	8	3,6%
6	Social Phobia	4	1,8%
7	Generalized Anxiety Disorder	29	12,9%
8	Specific Phobia	4	1,8%
9	Obsessive Compulsive Disorder	16	7,1%
10	Enuresis	2	0,9%
12	Anorexia Nervosa	1	0,4%
14	Attention Deficit and Hyperactivity Disorder	57	25,4%
15	Oppositional Defiant Disorder	2	0,9%
16	Conduct Disorder	9	4,0%
17	Tic Disorder	5	2,2%
18	Post Traumatic Stress Disorder	10	4,5%
	Total	256	114,3%
	Number of Patients with Two Diseases	32	14,3%
	Total Number of Patients	224	100,0%

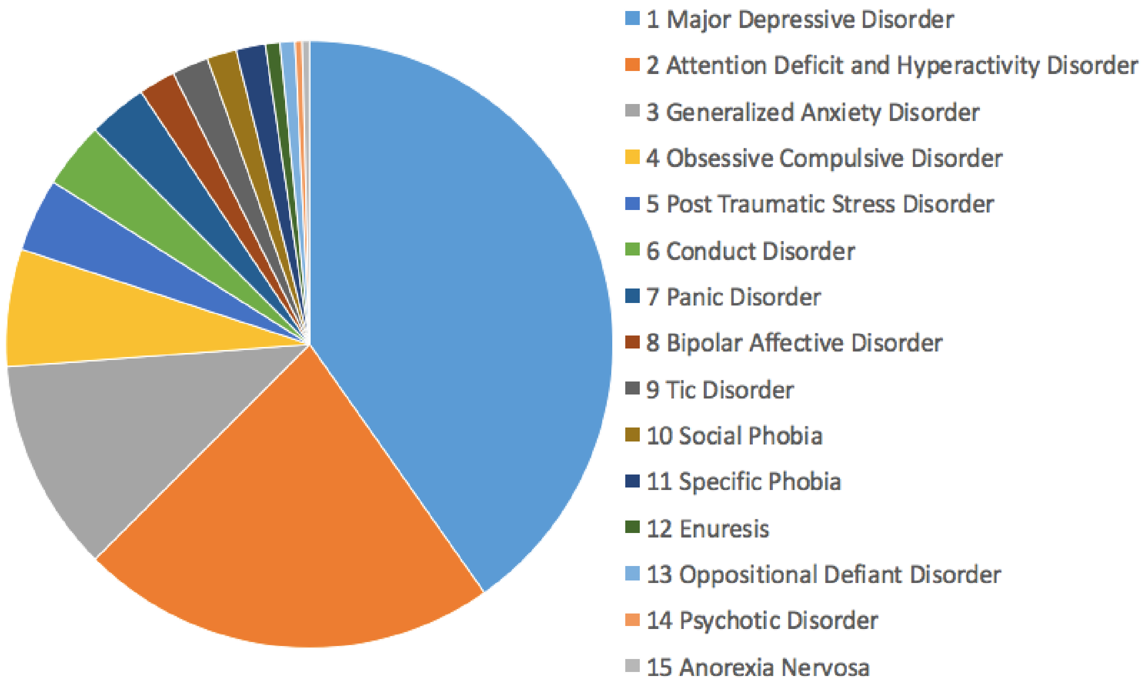

Figure 11: Diagnosis of The Respondents

Demographics

In our sample, there were 132 (58.9%) female patients and 92 (41.1%) male patients.

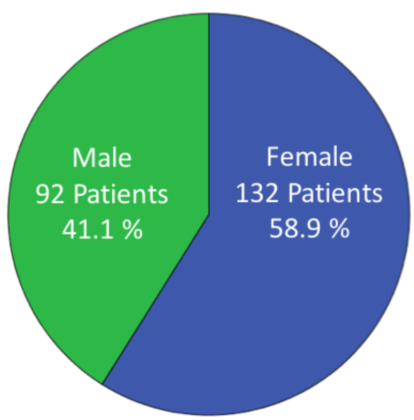

Figure 12: Gender of Patients

The relationship between gender of patients and their diagnosis were examined using chi-square test. The result of the test can be seen on the table below. Female patients with major depressive disorder had statistically significantly higher incidence level than male patients. On the other hand, male patients with ADHD had statistically significantly higher incidence level than female patients. In terms of the incidence of generalized anxiety disorder, there were no statistically significant difference between female and male patients. The findings were inline with the literature (Aktepe et al. 2010; Akdemir and Cetin 2008; Aras et al. 2007; Ucar et al. 2014; Durukan et al. 2011).

Table 5: The Relationship Between Gender of Patients and Their Diagnosis

	Major Depressive Disorder	**ADHD**	**Gen. Anxiety Disorder**
Male (n=92)	21	43	11
Female (n=132)	82	14	18
Total	103	57	29
Chi-Square Test Asymptotic Significance (2-sided)	0.000	0.000	0.713

Our sample had an average age of 15.53 and standard deviation of 1.72. The minimum age was 12 and maximum age was 18 as expected.

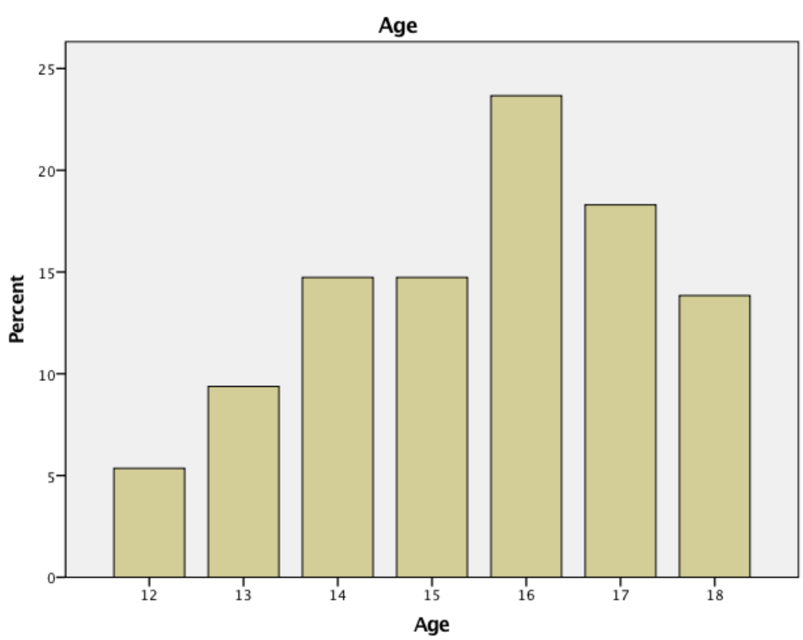

Figure 13: Age of Patients

As a result of the question regarding parental status, 190 (84.8 %) patients had their parents married. 23 (10.3 %) of the parents were divorce, 10 (4.5 %) of the patients lost their father, and one (0.4 %) of the patient lost her mother.

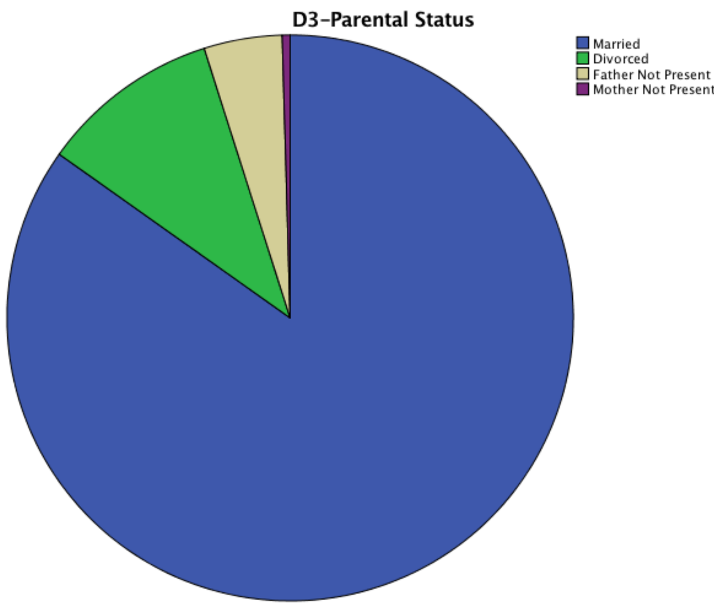

Figure 14: Parental Status of Patients

When the age of parents examined, it is observed that mothers had a mean of 42.22 and standard deviation of 6.4. The youngest mother was 29 years old and the oldest one was 61. Fathers, on the other hand, had a mean of 46.33 and standard deviation of 6.77. The youngest father was 31 years old and the oldest one was 71. The distribution of the age of parents can be seen the figure below. The peaks at the ages of 40, 45, and 50 were observed for both parents age. This was probably because the respondents were not sure about their parents' age, so they provided an approximate number.

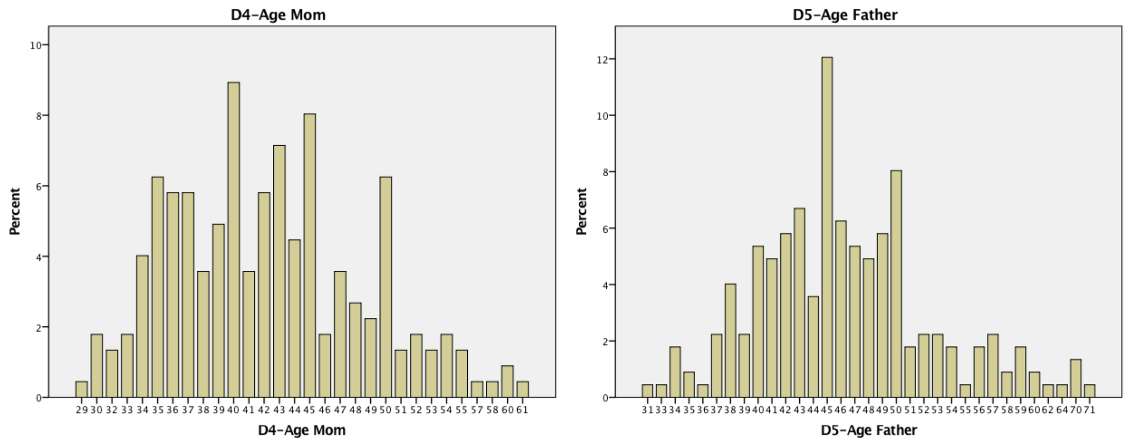

Figure 15: Age of Parents

In terms of education level of parents, the result can be seen in the table and the figure below.

Table 6: Education Level of Parents

	Mother's Education		Father's Education	
	Frequency	Percent	Frequency	Percent
Never went to school	34	15.2	17	7.6
Primary school	96	42.9	70	31.3
Middle School	39	17.4	44	19.6
High School	31	13.8	53	23.7
University	24	10.7	40	17.9
Total	224	100.0	224	100.0

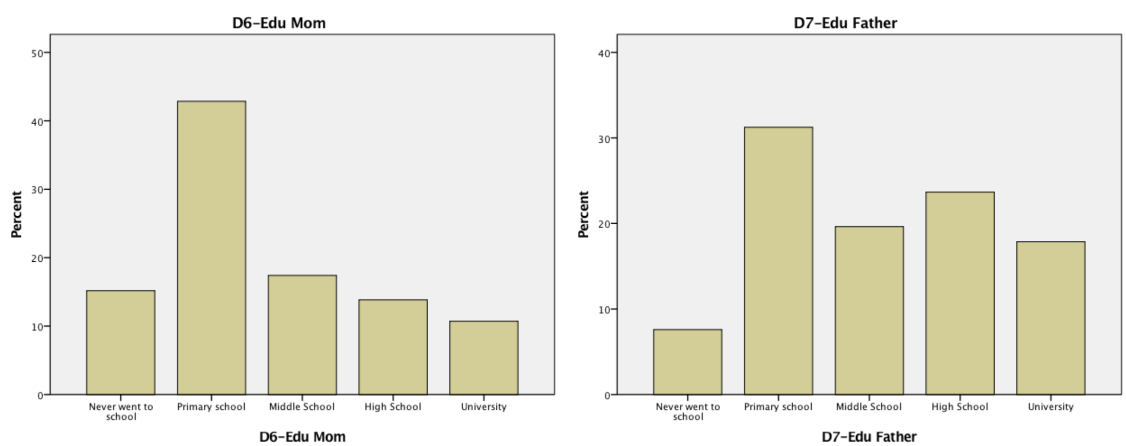

Figure 16: Education Level of Parents

Employment situations of the parents can be seen in the table and the figure below.

Table 7: Employment Situation of Parents

	Mother's Employment		Father's Employment	
	Frequency	Percent	Frequency	Percent
Not employed	164	73.2	47	21.0
Full-time employed	50	22.3	153	68.3
Retired	10	4.5	24	10.7
Total	224	100.0	224	100.0

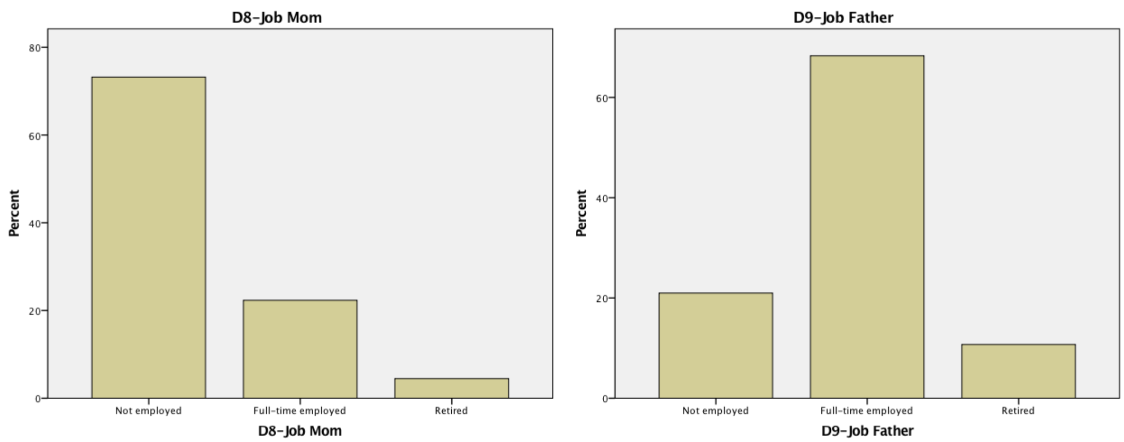

Figure 17: Employment Situation of Parents

Perceived monthly income of patient's family can be seen in the table and figure below.

Table 8: Perceived Monthly Income of The Family

	Frequency	Percent
1000TL or less	86	38.4
1000TL-3300TL	94	42.0
3300TL or more	44	19.6
Total	224	100.0

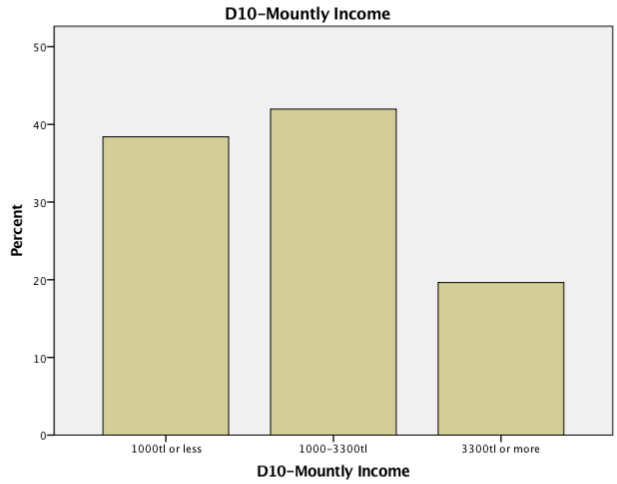

Figure 18: Perceived Monthly Income of The Family

The number of siblings of the patients is presented in the table and figure below.

Table 9: Number of Siblings of The Patients

Number of Siblings		
	Frequency	Percent
1	27	12.1
2	75	33.5
3	56	25.0
4	27	12.1
5 or more	39	17.4
Total	224	100.0

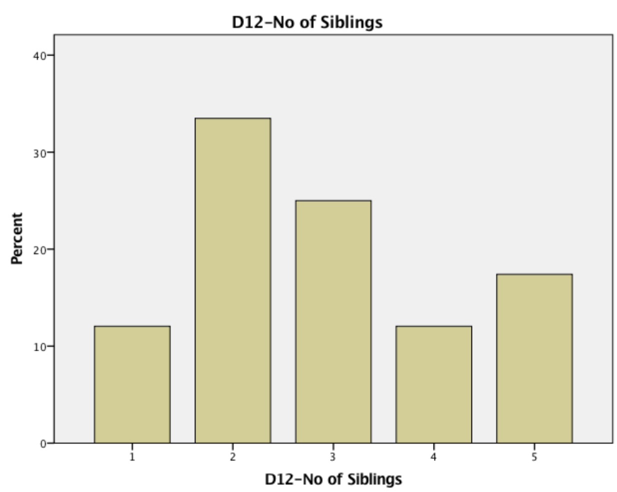

Figure 19: Number of Siblings of The Patients

The birth order of the patients is presented in the table and figure below.

Table 10: Birth Order of Patients Among Their Siblings

	Frequency	Percent
1st	104	46.4
2nd	61	27.2
3rd	24	10.7
4th	12	5.4
5th or more	23	10.3
Total	224	100.0

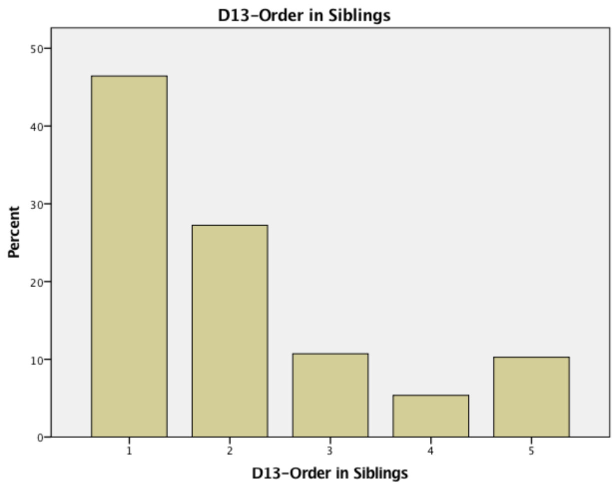

Figure 20: Birth Order of Patients Among Their Siblings

The results of the questions regarding the patient's house members can be seen in the table below. The house member results were compared with parental status results using a cross table, which can be seen below. The comparison suggests that patients with married parent mostly live with their parents except 2 patients were living with one of their parents and 12 patients were living without their parents. Due to the consistency between the two results, only parental status variable will be used in the analysis of this study.

Table 11: House Members of The Patients

	Frequency	Percent
Living with Both Parents	176	78.6
Living with One of The Parents	31	13.8
Living without Parents	17	7.6
Total	224	100.0

Table 12: Cross Table: House Members vs. Parental Status

	Parental Status		
	Divorced	Married	Total
Living with Both Parents	0	176	176
Living with One of The Parents	29	2	31
Living without Parents	5	12	17
Total	34	190	224

The results of the questions regarding physiological and psychological chronical diseases of the respondents are reported in the tables below. The chronical diseases reported by the respondents were diverse in terms of the effects of diseases on daily life such as allergies and diabetes. Because considering these different diseases as one variable might be misleading, this result was not used as a control variable in our analysis.

Table 13: Physiological Chronical Diseases

	Frequency	Percent
Not Have	180	80.4
Have	44	19.6
Total	224	100.0

Table 14: Psychological Chronical Diseases

	Frequency	Percent
Not Have	194	86.6
Have	30	13.4
Total	224	100.0

Control Variables of Diseases and Demographics

As mentioned in the conceptual model, the two control variables in the study was diseases and demographics. At this point of the report, each variable in the two main categories is examined to be used as a control variable. If a variable takes a value with an incidence of less than 20, then it is considered as statistically not enough so not possible to control for that value. All the variables presented above were evaluated and control variables and their possible values were selected. Three diseases and twelve demographic variables were selected and a total of 15 control variables was selected.

Table 15: Control Variables of Diseases and Demographics

Category	**Control Variable Name**	**Value of The Variable**
Diseases	Major Depressive Disorder	1 if diagnosed 0 if not diagnosed
	Attention Deficit and Hyperactivity Disorder	
	Generalized Anxiety Disorder	
Demographics	Gender of Patients	1 if female; 0 if male
	Age of Patient	Patient’s age
	Parental Status	1 if married; 0 if else
	Age of Mother	Mother’s age
	Age of Father	Father’s age
	Mother’s Education Level	1 if never went to school; 2 if primary school; 3 if middle school; 4 if high school; 5 if university
	Father’s Education Level	
	Mother’s Employment Situation	1 if employed or retired; 0 if unemployed
	Father’s Employment Situation	
	Perceived Monthly Income of The Family	1 if 1000TL or less; 2 if 1000TL-3000TL; 3 if 3300TL or more
	Number of Siblings	1; 2; 3; 4; 5 or more
	Birth Order Among Siblings	1^{st}; 2^{nd}; 3^{rd}; 4^{th}; 5^{th} or more

Sample Comparison with Turkish Population

The target population of our survey was decided as adolescents who are aged between 12 and 18, and apply to a child and adolescent psychiatry clinic in Turkey. We were able to draw 224 patients as our sample from the target population. A comparison of the target population and our sample in terms of diseases and demographic variables must be conducted in order to understand whether the sample accurately represents the population.

Regarding the values of the control variables for the population, a literature search was conducted. In spite of an extensive literature search, we could not find a report or study using the administrative data of all the child and adolescent psychiatry clinics in Turkey. Therefore, it will not be possible to statistically compare our sample with the target population. Instead, there are retrospective studies which uses the data of patients who apply to specific outpatient clinics in Turkey. The results of these studies are compared with our study in terms of the diseases and demographic variables. The comparison can be seen in the table below. The location of each clinic that each study was conducted at must be considered when evaluating representativeness of the study's sample. Our sample was collected in Bursa, which is the city that our study was conducted, and demographics of the city must be considered.

Table 16: Sample Comparison with Other Retrospective Studies

Control Variable Name		This Study	Akdemir and Cetin (2008)	Aktepe and colleagues (2010)	Aras and Colleagues (2007)	Ucar and colleagues (2014)	Durukan and colleagues (2011)
Target Age of The Study		12-18	12-19	1-18	1-18	1-18	1-18
Major Depressive Disorder		46.0%	13.5%	15.7% *	7.5%	38% *	15.7% *
Attention Deficit and Hyperactivity Disorder		25.4%	24.0%	12.0% *	13.0%	10% *	32.8% *
Generalized Anxiety Disorder		12.9%	15.0%	10.0% *	9.1%	11% *	12.8% *
Gender of Patients		58.9 % Female	45.8% female	35.4% female	36.4% female	51.9% female *	41.3% female
Age of Patient		15.5 ± 1.7	14.1 ± 1.6			9,5 ± 4,6	
Parental Status		84.8% married	88.8 % married	94% married	87.5% married		
Age of Mother		42.2 ± 6.6	40,2 ± 5,4	35.1 ± 6.2	36.9 ± 6.2		
Age of Father		46.3 ± 6.7	44,0 ± 5,8	38.9 ± 6.9	41.0 ± 6.5		
Mother's Education Level	never went to school	15.2%	2.9%	1.7%	1.8%		
	primary school	42.9%	35.0%	47.8%	23.1%		
	middle school	17.4%	11.8%	6.2%	7.6%		
	high school	13.8%	27.1%	27.3%	31.6%		
	university	10.7%	23.2%	17%	35.9%		
Father's Education Level	never went to school	7.6%	0%	0.8%	0.3%		
	primary school	31.3%	13.2%	29.5%	13.1%		
	middle school	19.6%	10.6%	12.3%	10.9%		
	high school	23.7%	31.3%	27.4%	29.1%		
	university	17.9%	44.9%	30%	46.7%		
Mother's Employment Situation		73.2% unemployed	63.4% not employed	73.9% unemployed	48.3% unemployed		
Father's Employment Situation		21.0% unemployed	2.4% not employed	3% unemployed	1.8% unemployed		
Perceived Monthly Income of The Family	1000TL or less	38.4%					
	1000TL-3300TL	42.0%					
	3300TL or more	19.6%					
Number of Siblings	1	12.1%		20.4%	33.4%	25.8%	
	2	33.5%		53.6%	53.5%	46.1%	
	3	25.0%		21.5%	10.4%	19.6%	
	4	12.1%		2.9%	1.8%	6.2%	
	5 or more	17.4%		1.6%	1.0%	2.3%	
Birth Order Among Siblings	1st	46.4%		55.8%	61.6%	54.9%	
	2nd	27.2%		32.8%	31.5%	31.2%	
	3rd	10.7%		8.5%	5.9%	10.0%	
	4th	5.4%		2.1%	0.8%	2.9%	
	5th or more	10.3%		0.8%	0.1%	1.0%	

As a result of papers in the table above, it is reported that the incidence of major depressive disorder among female adolescents is statistically significantly higher than the incidence among males. The age of adolescents with major depressive disorder is also statistically significantly higher than the age of adolescents with other diseases. On the other hand, the incidence of ADHD among males is statistically significantly higher that the incidence of ADHD among females. The age of ADHD patients is also statistically significantly lower than the age of patients with other diseases. This explains relatively high major depressive disorder incidence and high female rate in our sample. Average age of our sample is higher due to the target age of our study. The difference in the other variables related to parents and siblings can be explained by the demographics of the city in which our study was conducted.

Comparison of Excluded and Included Results

At the end of survey application, 273 survey results were collected. 49 of them were excluded due to missing parts and conflicting answers, so 224 of them were included for the analysis. The comparison of these included and excluded results must be conducted in order to evaluate non-response bias. The main logic behind non-response bias is that whether there is a factor that explains why some adolescents did not fill the questionnaires properly. The comparison was conducted in terms of the diseases and demographic variables.

Numeric control variables which are age of patients, father, and mother were assessed for normality with Kolmogorov-Smirnov Test and the Shapiro-Wilk Test. The results of tests, which can be seen below, showed that the variables except excluded age of father and mother are not normally distributed. Therefore, Wilcoxon-Mann-Whitney test used for comparisons instead of t-test.

Table 17: Normality Test Results of Numeric Variables

Tests of Normality

		Kolmogorov-Smirnov			Shapiro-Wilk		
	Inclusion	Statistic	df	Sig.	Statistic	df	Sig.
Age of Mother	Excluded	.111	49	.175	.944	49	.021
	Included	.082	224	.001	.979	224	.002
Age of Father	Excluded	.073	49	.200*	.986	49	.822
	Included	.107	224	.000	.953	224	.000
Age of Patient	Excluded	.201	49	.000	.905	49	.001
	Included	.167	224	.000	.933	224	.000

The result of Wilcoxon-Mann-Whitney test for the numeric control variables can be seen in the table below. The result suggests that there is not a statistically significant difference between included and excluded group in terms of age of patient, father, and mother.

Table 18: Comparison Results of Numeric Variables

Test Statistics

	Age of Patient	Age of Mother	Age of Father
Mann-Whitney U	4639.500	5175.000	4933.000
Wilcoxon W	5864.500	30375.000	30133.000
Z	-1.720	-.626	-1.111
Asymp. Sig. (2-tailed)	.085	.531	.267

The rest of the variables are categorical or nominal variables, therefore, chi-square test used for comparisons of the two groups. The only statistically significantly different variables for the two group were major depressive disorder and attention deficit and hyperactivity disorder. This results can be explained by the nature of ADHD patients, who are having problems with focusing on exams and homework. The rest of the variables were not statistically significantly different for the two group. Considering enough number of ADHD patients in our sample, it can be concluded that non-response bias was not a serious issue for our sample.

Table 19: Comparison Results of Categorical and Nominal Variables

Control Variable	Chi-Square Test			Comment
	Value	**df**	**Asymptotic Significance (2-sided)**	
Major Depressive Disorder	4.977	1	0.026	Statistically significantly less MDD patients in the excluded group
ADHD	5.972	1	0.015	Statistically significantly more ADHD patients in the excluded group
Gen. Anxiety Disorder	0.018	1	0.894	Statistically insignificant difference between the groups
Gender of Patient	1.029	1	0.310	Statistically insignificant difference between the groups
Parental Status	0.813	1	0.367	Statistically insignificant difference between the groups
Mother's Education Level	7.439	4	0.114	Statistically insignificant difference between the groups
Father's Education Level	3.925	4	0.416	Statistically insignificant difference between the groups
Mother's Employment Situation	0.393	1	0.531	Statistically insignificant difference between the groups
Father's Employment Situation	0.542	1	0.462	Statistically insignificant difference between the groups
Perceived Monthly Income of The Family	0.965	2	0.617	Statistically insignificant difference between the groups
Number of Siblings	5.939	4	0.204	Statistically insignificant difference between the groups
Birth Order Among Siblings	4.094	4	0.393	Statistically insignificant difference between the groups

The Amount of Internet Use

The use of internet frequency through computer, smart phone, and tablet channels were asked to respondents in the questionnaire. The results can be seen in the table and figures below.

Table 20: The Amount of Internet Use

	Computer		Smart Phone		Tablet	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
None	108	48.2	46	20.5	154	68.8
Less than 5 hours weekly	29	12.9	6	2.7	18	8.0
less than 2 hour daily	23	10.3	29	12.9	21	9.4
1-3 hours daily	29	12.9	45	20.1	13	5.8
4-5 hours daily	16	7.1	36	16.1	7	3.1
more than 6 hours daily	19	8.5	62	27.7	11	4.9
Total	224	100.0	224	100.0	224	100.0

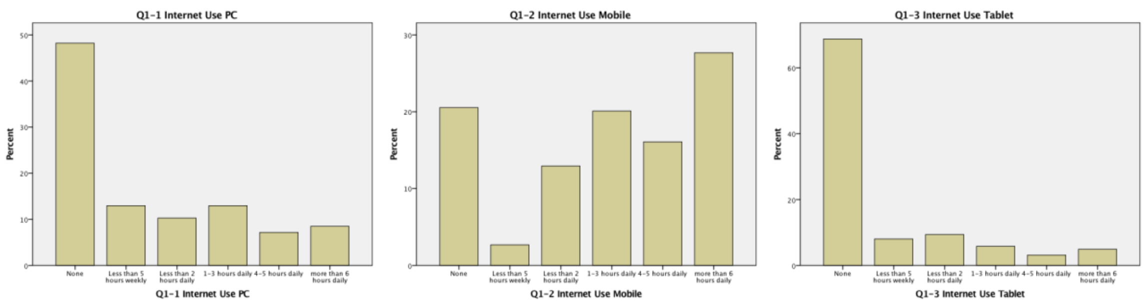

Figure 21: The Amount of Internet Use

With the purpose of obtaining a value for the amount of internet use variable in the conceptual model, the average internet use was calculated. The average should be interpreted as a scale that 1 corresponds to no internet use, and 6 corresponds to an internet use of more than 6 hours daily. The resulting average internet use was 2.72 ± 1.02 for our sample and the distribution of average internet use can be seen in the figure below.

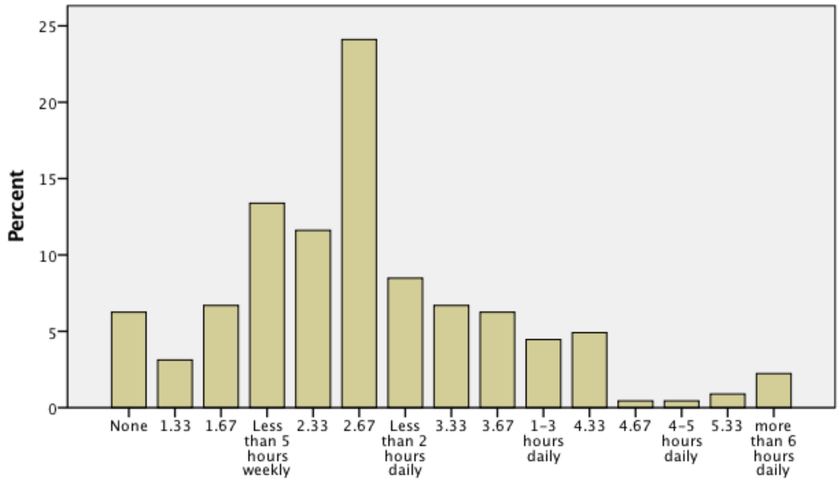

Figure 22: Average Amount of Internet Use

To understand the effects of the diseases and demographic variables on the amount of internet use, four regression analyses were conducted with the diseases and demographic variables as independent variables. Internet use through each channel and average internet use was defined as the dependent variable of each regression analysis. The result of these analysis can be seen below. Model 1, model 3, and model 4 were statistically insignificant. Therefore, the variables had no statistically significant effects on average internet use and internet use through computer and tablet. On the other hand, model 2 was significant with an adjusted R square value of 0.147. The coefficients of model 3 are given in the table below. Generalized anxiety disorder, age of patient, mother, and father were significant variables. Having GAD diagnosis positively affected mobile internet use. As the age of patient increased, the amount of mobile internet use increased. Although ages of parents were also significant, their effects were relatively low and their effects were in the opposite directions.

Table 21: Regression Models for Control Variables

	Model Summary				ANOVA					
	R	R Square	Adjusted R Square	Std. Error of the Estimate		Sum of Squares	df	Mean Square	F	Sig.
Model 1: Computer Channel	.325	.106	.041	1.676	Regression	69.020	15	4.601	1.639	.066
					Residual	583.976	208	2.808		
					Total	652.996	223			
Model 2: Smart Phone Channel	.452	.204	.147	1.693	Regression	153.137	15	10.209	3.561	.000
					Residual	596.252	208	2.867		
					Total	749.388	223			
Model 3: Tablet Channel	.305	.093	.027	1.414	Regression	42.537	15	2.836	1.419	.140
					Residual	415.588	208	1.998		
					Total	458.125	223			
Model 4: Average Internet Use	.322	.104	.039	1.00047	Regression	24.050	15	1.603	1.602	.075
					Residual	208.196	208	1.001		
					Total	232.246	223			

Table 22: Coefficients of The Variables in Model 2

Coefficients of Model 2 (Smart Phone Channel)					
	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	.915	1.385		.661	.509
Major Depressive Disorder	.441	.302	.120	1.459	.146
Attention Deficit and Hyperactivity Disorder	.190	.351	.045	.541	.589
Generalized Anxiety Disorder	.779	.385	.143	2.022	.044
Gender of Patients	.321	.266	.086	1.209	.228
Age of Patient	.245	.077	.230	3.179	.002
Parental Status	-.330	.332	-.065	-.994	.321
Age of Mother	.073	.034	.253	2.128	.035
Age of Father	-.078	.030	-.290	-2.602	.010
Mother's Education Level	-.049	.136	-.032	-.361	.718
Father's Education Level	-.118	.130	-.080	-.905	.366
Mother's Employment Situation	.536	.289	.130	1.850	.066
Father's Employment Situation	-.114	.316	-.025	-.361	.719
Perceived Monthly Income of The Family	.337	.215	.136	1.569	.118
Number of Siblings	-.134	.161	-.093	-.833	.406
Birth Order Among Siblings	-.135	.163	-.097	-.831	.407

The Amount of Health Search

For the amount of health search online, the respondents were asked six questions. A point scale system is created for presenting and analyzing the result of this part. The meanings of the points in the scale system can be seen in the table below. The results of the six questions can be seen in the figures below. The average of the six questions was calculated as a value of this variable in the conceptual model. The average was 2.45 ± 1.23 and its distribution can be seen in the figure below.

Table 23: The Meanings of Points in The Scale System

1	Never
2	No but Interested
3	Yes, Rarely
4	Yes, Sometimes
5	Yes, Frequently

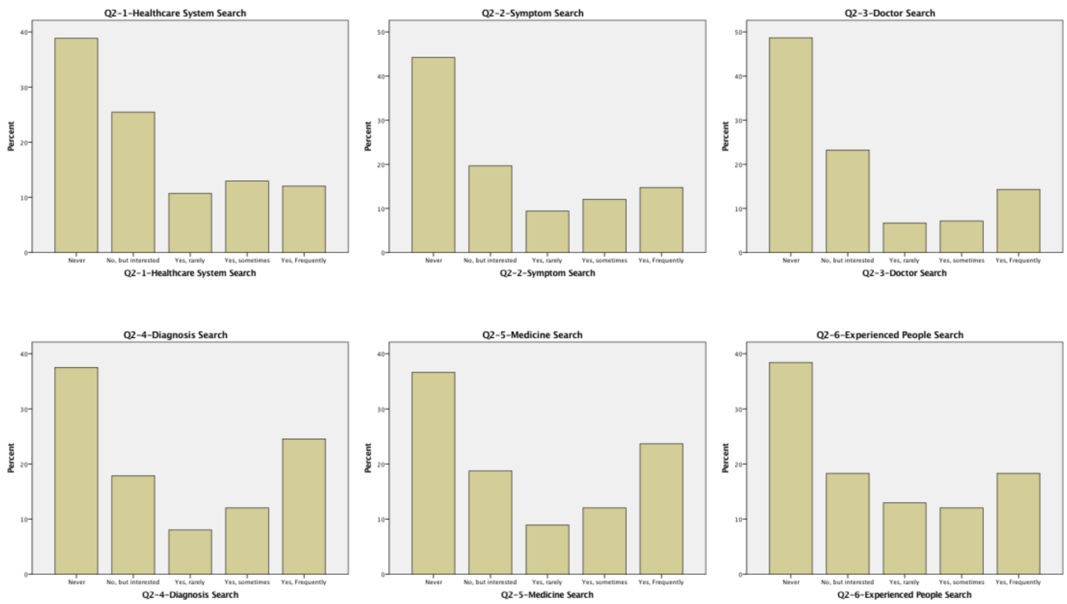

Figure 23: The Amount of Health Search

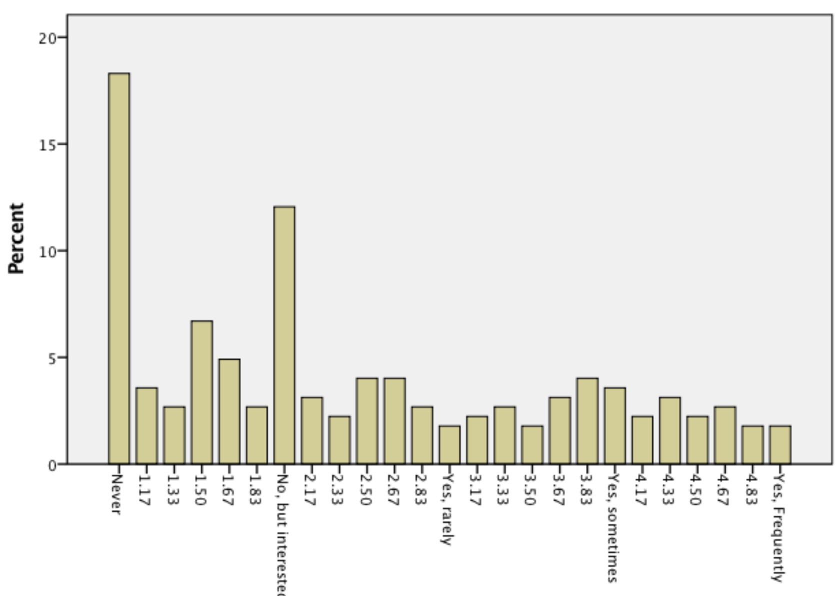

Figure 24: Average Amount of Health Search

Assessing the effects of the diseases and demographic variables on the results of the amount of health search was analyzed by conducting seven regression models with the diseases and demographic variables as independent variables. For each model, each question and the average health search was defined as dependent variable. All the regression models were statistically insignificant except the model for the question about people with similar conditions to learn about their experiences. The result of the model and significant variables in the model are reported in table below. Having ADHD diagnosis affect negatively the search about this topic. Education level of mother is positively correlated with the search. Finally, income level also showed a positive effect on the search about the topic.

Table 24: Significant Regression Model for Control Variables

	Model Summary				ANOVA					
	R	R Square	Adjusted R Square	Std. Error of the Estimate		Sum of Squares	df	Mean Square	F	Sig.
Model 6: Search of Experienced People	.353	.125	.061	1.49037	Regression	65.703	15	4.380	1.972	0.019
					Residual	462.011	208	2.221		
					Total	527.714	223			

Table 25: Coefficients of The Significant Variables in Model 6

Coefficients of Model 6 (Search of Experienced People)					
	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Attention Deficit and Hyperactivity Disorder	-.653	.309	-.185	-2.114	.036
Mother's Education Level	.279	.119	.219	2.337	0.020
Perceived Monthly Income of The Family	.545	.189	.262	2.883	0.004

Regarding healthcare related content creation on blogs, forums, and social media sites; there were six question which were similar to health related search questions. Although extensive explanations for the meaning of content were provided, the results showed that 82% of adolescents in our sample said they never create content.

Considering the results from other parts of the questionnaire such their Instagram and Snapchat use, also content creation amount in Turkey; this results were interpreted as respondents did not understand this part of the questionnaire. Therefore, the results from this part will not be used in analysis and testing the conceptual model with the logic of not using suspicious data.

Table 26: Healthcare Content Creation

	Frequency	Percent
1-Never	184	82.1
2-Sometimes	27	12.1
3-Frequently	13	5.8
Total	224	100.0

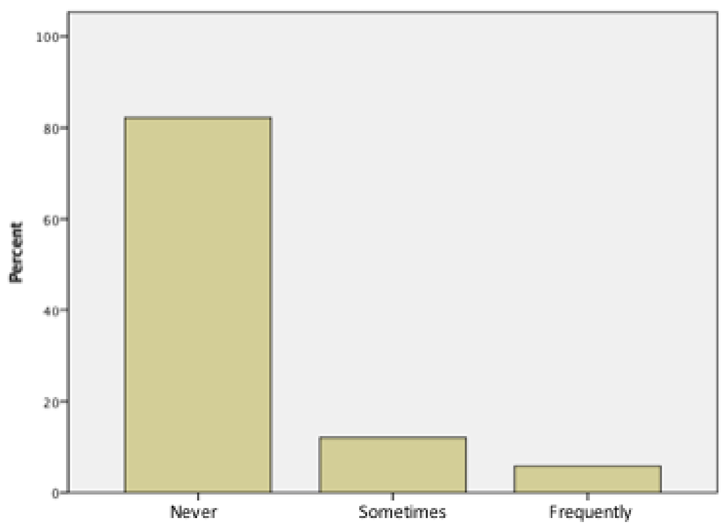

Figure 25: Healthcare Content Creation

Health Search Abilities

In this part of the questionnaire, four questions in 1-7 Likert scale format were asked to respondents. The answers to the four questions are summarized in the table and figures below. Average Likert score of the four questions was 3.22 ± 2.08 and its distribution can be seen in the figure below. As one can see, around 18% of the respondents expressed that they do not possess health search abilities.

Table 27: Health Search Abilities

	Reaching Information Sources		Distinguishing Valuable Information		Finding Comprehensive Information		Decision Making Based on Information Found	
	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
Strongly Disagree	82	36.6	73	32.6	95	42.4	114	50.9
Disagree	27	12.1	33	14.7	29	12.9	16	7.1
Partially Disagree	15	6.7	14	6.3	14	6.3	16	7.1
Neutral	9	4.0	21	9.4	16	7.1	9	4.0
Partially Agree	21	9.4	23	10.3	20	8.9	11	4.9
Agree	33	14.7	32	14.3	30	13.4	34	15.2
Strongly Agree	37	16.5	28	12.5	20	8.9	24	10.7
Total	224	100.0	224	100.0	224	100.0	224	100.0

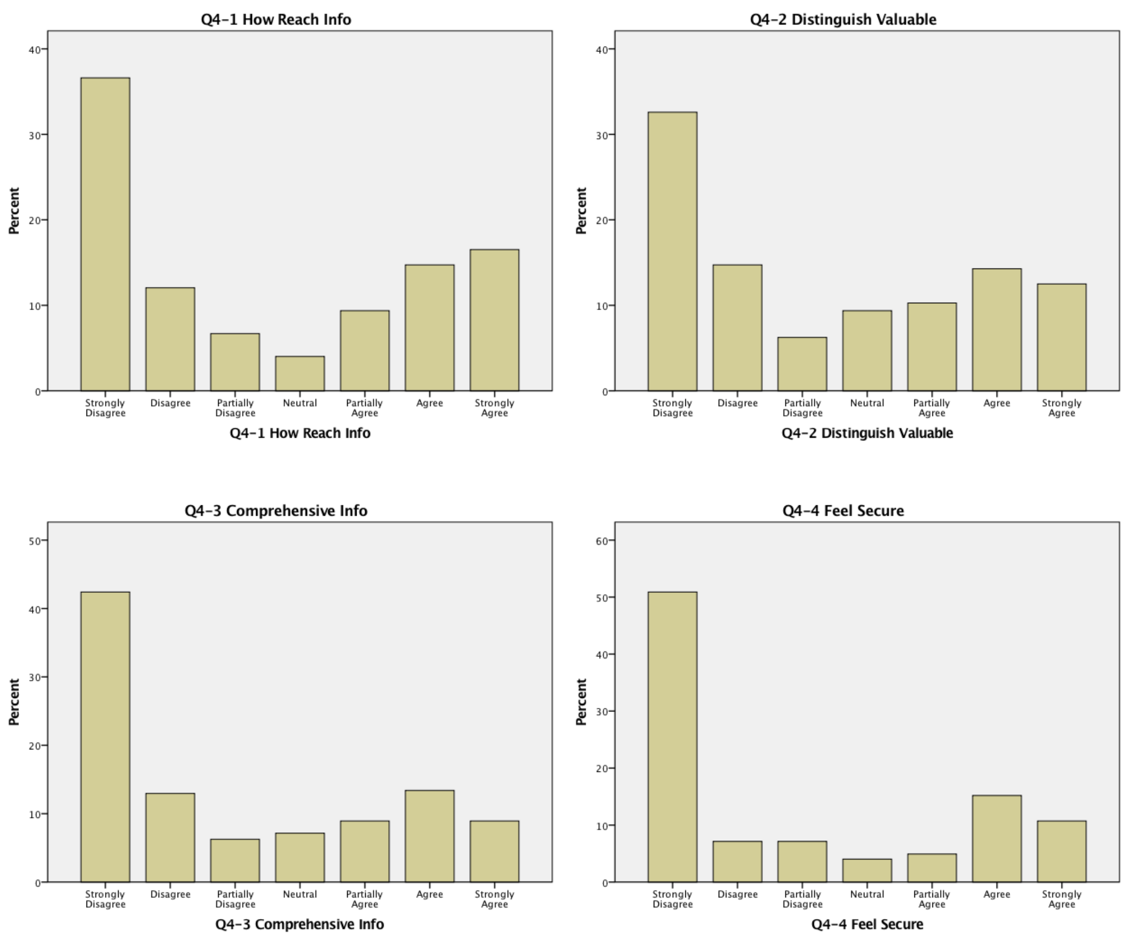

Figure 26: Health Search Abilities

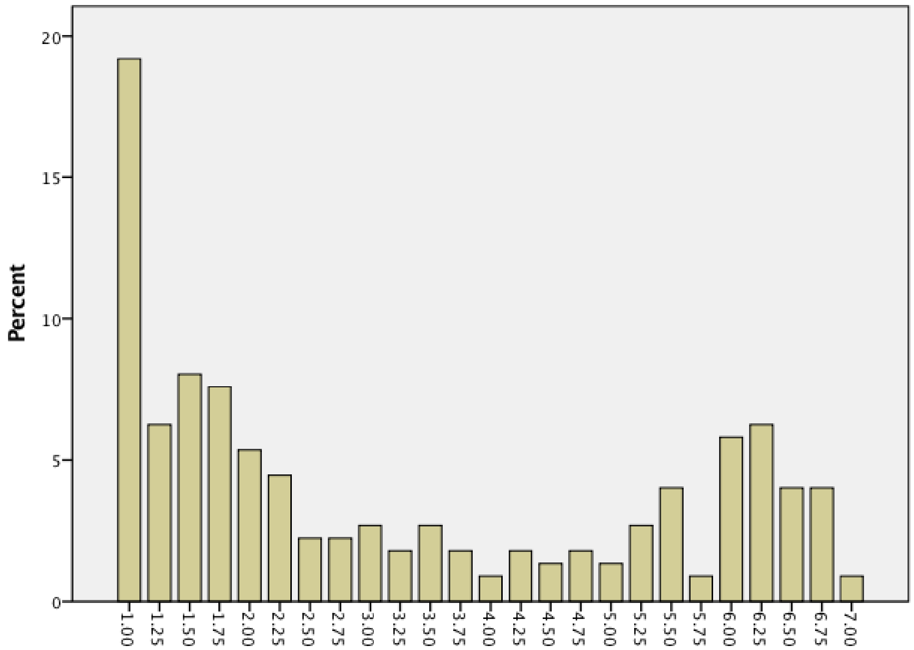

Figure 27: Average Health Search Abilities

Table 28: Meanings of The Points in Likert Scale

1-Strongly Disagree
2-Disagree
3-Partially Disagree
4-Neutral
5-Partially Agree
6-Agree
7-Strongly Agree

Evaluating the effects of the diseases and demographic variables on the results of health search abilities was analyzed by conducting five regression models with the diseases and demographic variables as independent variables. For each model, each question and the average health search ability was defined as dependent variable. All the regression models were statistically significant except the model 4, which had the dependent variable of decision making based on information found online. Significant variables of the significant models are reported in the table below. For all of them, mother's education level was significant and positively contributed to health search abilities. Having ADHD diagnosis negatively affects health search abilities in the first model. On the contrary, having MDD diagnosis positively affects health search abilities in the third model. Income level was another significant variable in the third model, and it also positively affects health search abilities.

Table 29: Significant Regression Model for Control Variables

	Model Summary				ANOVA					
	R	R Square	Adjusted R Square	Std. Error of the Estimate		Sum of Squares	df	Mean Square	F	Sig.
Model 1: Reaching Information Sources	.355	.126	.063	2.324	Regression	162.266	15	10.818	2.003	.016
					Residual	1123.623	208	5.402		
					Total	1285.888	223			
Model 2: Distinguishing Valuable Information	.360	.129	.067	2.177	Regression	146.636	15	9.776	2.062	.013
					Residual	986.222	208	4.741		
					Total	1132.857	223			
Model 3: Finding Comprehensive Information	.366	.134	.071	2.135	Regression	146.269	15	9.751	2.138	.010
					Residual	948.512	208	4.560		
					Total	1094.781	223			
Model 4: Decision Making Based on Information Found	.329	.109	.044	2.281	Regression	131.777	15	8.785	1.688	.055
					Residual	1082.219	208	5.203		
					Total	1213.996	223			
Model 5: Average Health Search Abilities	.365	.133	.071	2.00981	Regression	129.019	15	8.601	2.129	.010
					Residual	840.184	208	4.039		
					Total	969.203	223			

Table 30: Coefficients of The Significant Variables in The Models

Significant Coefficients of Models						
Models	Control Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
Model 1	Attention Deficit and Hyperactivity Disorder	-.997	.482	-.181	-2.069	.040
	Mother's Education Level	.499	.186	.252	2.681	.008
Model 2	Mother's Education Level	.582	.174	.312	3.337	.001
Model 3	Major Depressive Disorder	.787	.381	.178	2.066	.040
	Mother's Education Level	.388	.171	.212	2.270	.024
	Perceived Monthly Income of The Family	.590	.271	.197	2.179	.030
Model 5	Mother's Education Level	.452	.161	.262	2.806	.005

The Amount of SNSs Use

Regarding SNSs use of adolescents, the most used SNS was determined for each respondent. 106 respondents answered that they use Facebook the most. Instagram and SnapChat were the following websites with 52 and 15 respondents respectively. On the contrary, 35 respondents reported that they did not use any SNS. The result of respondents' the most used SNSs can be seen in the table and figure below. For each respondent, the amount of the most used SNS was considered as their SNS use. The amount of SNSs use of adolescents in our survey can be seen in the table and figure below.

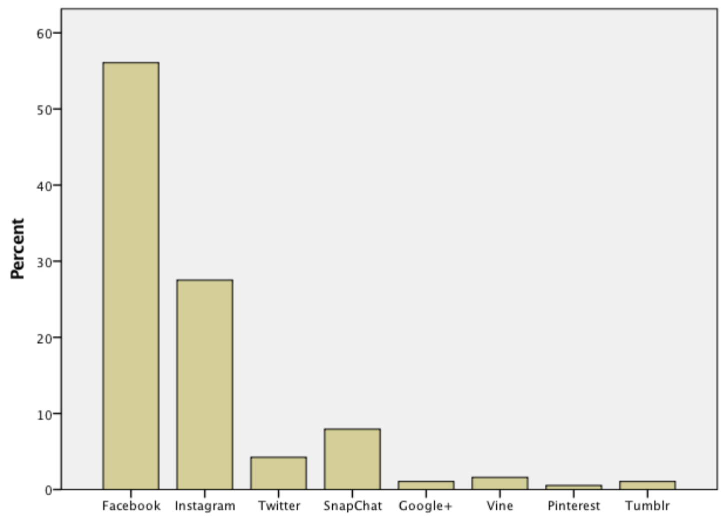

Figure 28: The Most Used SNSs

Table 31: The Most Used SNSs

Respondents' The Most Used SNSs		
	Frequency	Percent
1-Facebook	106	47.3
2-Instagram	52	23.2
3-Twitter	8	3.6
4-Snapchat	15	6.7
5-GooglePlus	2	.9
7-Vine	3	1.3
8-Pinterest	1	.4
10-Tumblr	2	.9
Total	189	84.4
Missing	35	15.6
Total	224	100.0

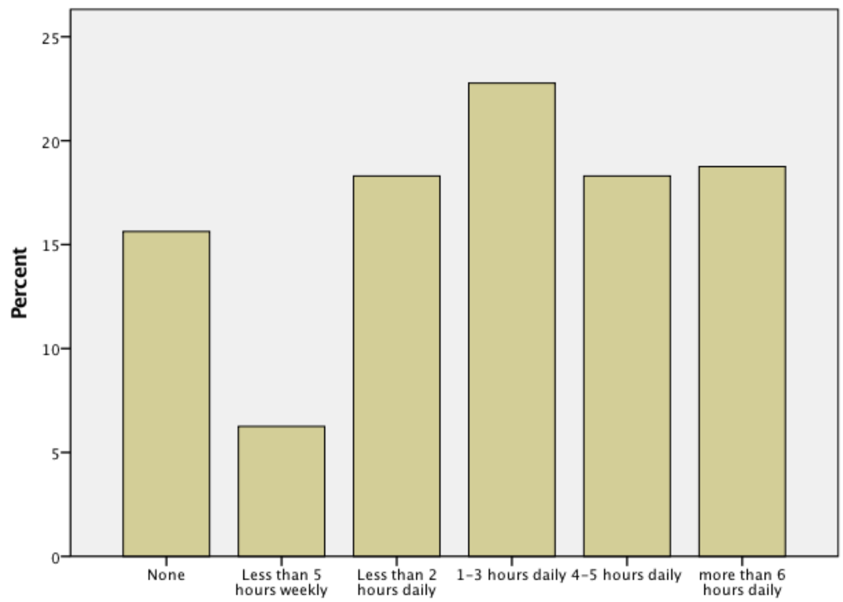

Figure 29: Combined Amount of SNSs Use

Table 32: Combined Amount of SNSs Use

	Frequency	Percent
1-Never	35	15.6
2- < 5 hours weekly	14	6.3
3-< 1 hour daily	41	18.3
4-1-3 hours daily	51	22.8
5-4-5 hours daily	41	18.3
6-> 6 hours daily	42	18.8
Total	224	100.0
Missing	0	

The diseases and demographic variables were controlled by one regression model with the amount of SNSs use defined as dependent variable. The result of the regression model and significant variables can be seen below. Patients with working mothers had used SNSs more. As the number of siblings increased, the amount of SNSs use decreased. This can be explained by having one tablet or computer or even smart phone for all siblings, which is a typical situation in Turkey.

Table 33: Significant Regression Model for Control Variables

	Model Summary				ANOVA					
	R	R Square	Adjusted R Square	Std. Error of the Estimate		Sum of Squares	df	Mean Square	F	Sig.
Model 1: The Amount of SNSs Use	.354	.125	.062	1.60207	Regression	76.426	15	5.095	1.985	.018
					Residual	533.855	208	2.567		
					Total	610.281	223			

Table 34: Coefficients of The Significant Variables in The Model

Significant Coefficients of Model 1					
Control Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Mother's Employment Situation	.559	.274	.150	2.040	.043
Number of Siblings	-.329	.152	-.254	-2.161	.032

Perceived Value of SNSs

There were four questions related to perceived value of SNSs in the questionnaire. The results of these questions, which were in Likert scale format, were averaged to obtain the perceived value of SNSs for each respondents. The perceived value of SNSs was 3.34 ± 2.11 and the distribution can be seen in the figure below.

Table 35: Meanings of The Points in Likert Scale

1-Strongly Disagree
2-Disagree
3-Partially Disagree
4-Neutral
5-Partially Agree
6-Agree
7-Strongly Agree

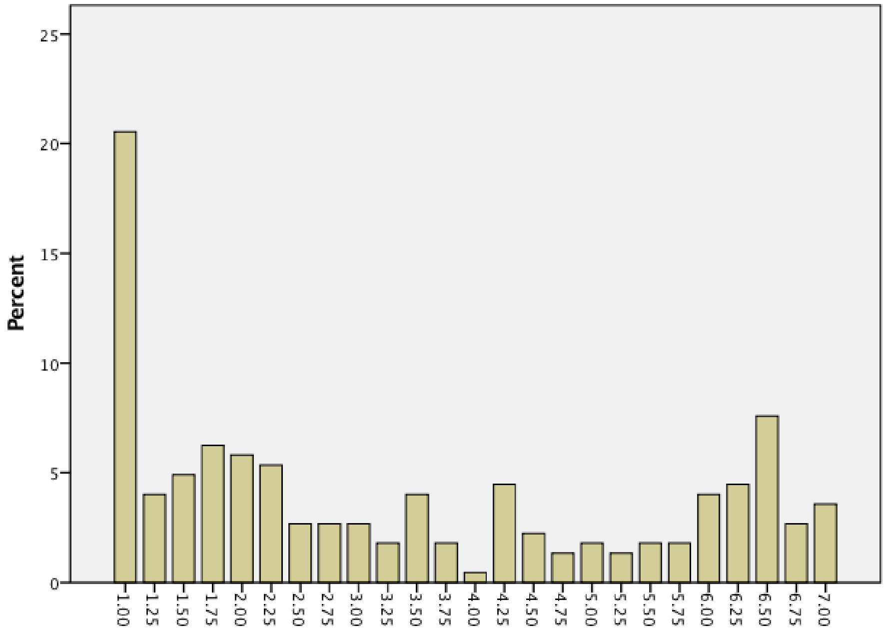

Figure 30: Averaged Perceived Value of SNSs

As a result of a regression model for determining the effects of the diseases and demographic variables on perceived value of SNSs, it found out that having MDD diagnosis strongly and positively affected the perceived value of SNSs. This can be interpreted as MDD patients find SNSs important in their fight with depression. The other significant variable in the regression model was the number of siblings which had a negative effect on perceived value of SNSs. This can be interpreted as having siblings might decrease the need online support and also access to internet might decrease because of having one device for all siblings. The result of the regression model can be seen below.

Table 36: Significant Regression Model for Control Variables

	Model Summary				ANOVA					
	R	R Square	Adjusted R Square	Std. Error of the Estimate		Sum of Squares	df	Mean Square	F	Sig.
Model 1: Perceived Value of SNSs	.379	.144	.082	2.01873	Regression	142.041	15	9.469	2.324	.004
					Residual	847.655	208	4.075		
					Total	989.696	223			

Table 37: Coefficients of The Significant Variables in The Model

Significant Coefficients of Model 1					
Control Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Major Depressive Disorder	.980	.360	.232	2.719	.007
Number of Siblings	-.426	.192	-.258	-2.221	.027

Perceived Psychological Safety on SNSs

There were four questions related to perceived psychological safety on SNSs in the questionnaire. The results of these questions, which were in Likert scale format, were averaged to obtain the perceived psychological safety on SNSs for each respondents. The average was 3.79 ± 1.95 and the distribution can be seen in the figure below.

Table 38: Meanings of The Points in Likert Scale

1-Strongly Disagree
2-Disagree
3-Partially Disagree
4-Neutral
5-Partially Agree
6-Agree
7-Strongly Agree

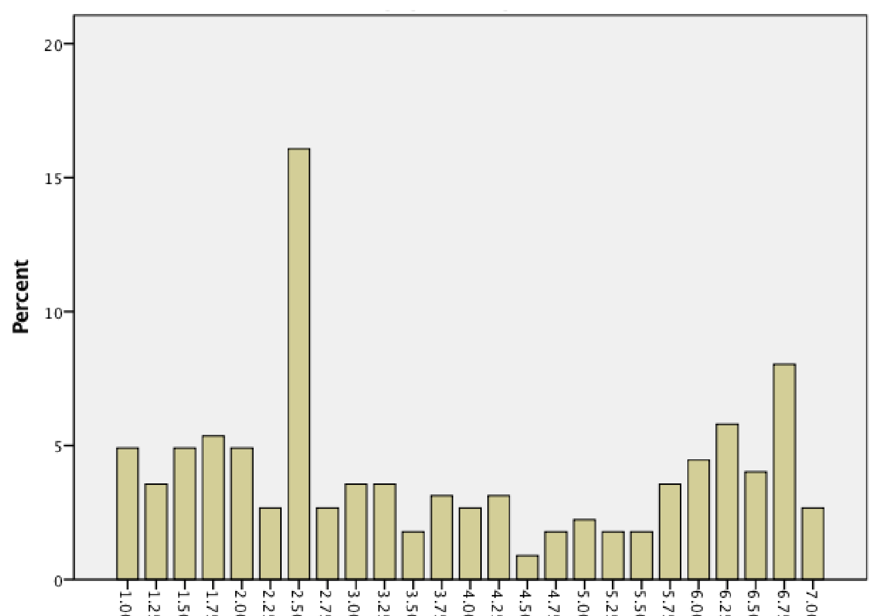

Figure 31: Averaged Perceived Psychological Safety on SNSs

As a result of a regression model for determining the effects of diseases and demographic variables on perceived psychological safety on SNSs, it found out that having MDD and/or GAD diagnosis strongly and positively affected the perceived psychological safety on SNSs. The result of the regression model can be seen below.

Table 39: Significant Regression Model for Control Variables

	Model Summary				ANOVA					
	R	R Square	Adjusted R Square	Std. Error of the Estimate		Sum of Squares	df	Mean Square	F	Sig.
Model 1: Perceived Value of SNSs	.337	.114	.050	1.89899	Regression	96.181	15	6.412	1.778	.039
					Residual	750.082	208	3.606		
					Total	846.263	223			

Table 40: Coefficients of The Significant Variables in The Model

Significant Coefficients of Model 1					
Control Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Major Depressive Disorder	1.11	.339	.286	3.293	.001
Generalized Anxiety Disorder	1.02	.432	.177	2.366	.019

Share of Symptoms on SNSs

For this part, 20 questions representing 20 symptoms were asked. For each question, respondents expressed the frequency of different SNS activities. A scale system was created to give points to each answer: 1 point corresponds to doing nothing, 2 points means sharing rarely, 3 points means sharing sometimes, and 4 means sharing frequently. Next, an average value was calculated for each question of each respondent. As the resulting means and standard deviation of each question can be seen below, the most activity was done when patients feeling happy and something good happens to them. On the other hand, the least activity was done when patients feel headache, stomachache or nausea. This is inline with the literature that says people share positive feeling more than negative feelings (Lin et al. 2014; Settanni and Marengo 2015; Denti et al. 2012). The average of the results of 20 question was calculated as 1.69 ± 0.83 which can be considered as average symptoms shares on SNSs. The distribution of average symptoms share on SNSs can be seen in the figure below. Around 28% of adolescent in our sample reported that they do not share their symptoms on SNSs while the rest of the sample share with varying frequency.

Table 41: Mean and Standard Deviation of Each Symptom

Descriptive Statistics		
	Mean	Std. Deviation
1-Happy	2.05	1.10
2-Betrayed	1.72	1.07
3-Everthing Will Be Bad	1.71	1.07
4-Peaceful	1.93	1.10
5-Health Concerns	1.55	0.99
6-Homework	1.55	0.98
7-Nervous	1.68	1.06
8-Self Confident	1.93	1.19
9-Angry	1.57	0.97
10-Treat Others Bad	1.51	0.90
11-Self Harm	1.49	0.94
12-Anxious	1.64	1.04
13-Traumatic	1.67	1.07
14-Headache	1.43	0.88
15-Scared	1.64	1.07
16-People Like Me	1.88	1.14
17-Bad Will Happen	1.58	1.00
18-Good Happens To Me	2.03	1.20
19-Feel Bad	1.62	1.04
20-People Treat Me Bad	1.54	0.97

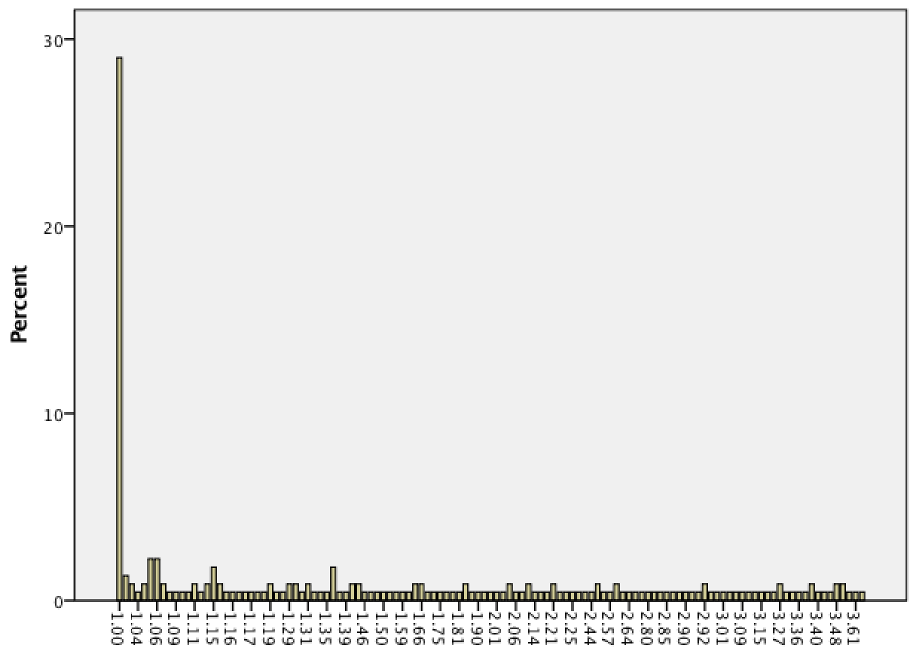

Figure 32: Share of Symptoms on SNSs

Assessment of diseases and demographic variables' effects showed that having MDD diagnosis and number of siblings were statistically significant. MDD patients shared more symptoms on SNSs. On the contrary, the increased number of siblings decreased symptom share. This was again related to having one device for all siblings in a Turkish family.

Table 42: Significant Regression Model for Control Variables

	Model Summary				ANOVA					
	R	R Square	Adjusted R Square	Std. Error of the Estimate		Sum of Squares	df	Mean Square	F	Sig.
Model 1: Symptom Share on SNSs	.404	.163	.103	.78485	Regression	25.024	15	1.668	2.708	.001
					Residual	128.125	208	.616		
					Total	153.150	223			

Table 43: Coefficients of The Significant Variables in The Model

Significant Coefficients of Model 1					
Control Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Major Depressive Disorder	.426	.140	.257	3.043	.003
Number of Siblings	-.161	.075	-.248	-2.159	.032

The average symptom share for each category of symptom was also calculated and reported in the table below. While depressive symptoms and traumatic events are the most shared category of symptoms, somatic complaints and self harm related symptoms remained the least shared symptoms by adolescents in our sample.

Table 44: Mean and Standard Deviation of Each Symptom Category

Statistics							
	Depressive Mood	Anxiety	Somatic Complaints	Suicidal Symptoms / Self Harm	Traumatic Events	Anger	Regret
Mean	1.78	1.67	1.49	1.49	1.71	1.57	1.51
Std. Deviation	0.90	0.85	0.84	0.94	0.90	0.97	0.90

Explanatory Factor Analysis

In this study, the survey was conduced to measure the control variables and the constructs of the conceptual model. While the measurement of the amount of internet use and SNSs use was straight forward, it is possible to ask the amount of use directly to the respondents. However, it is not possible to ask directly the concepts of health search abilities, perceived value of SNSs and psychological safety on SNSs. These concepts have to be measured by asking multiple questions covering the different aspects of each concept. In order to evaluate score validity and dimensionality of these concepts measured with multiple questions, explanatory factor analysis was conducted. Considering the size of our sample, confirmatory factor analysis was not conducted. The scholars do not suggest confirmatory factor analysis when the sample size is smaller than twenty times number of variables (Kline 2013).

Explanatory factor analysis was conducted by including all the questions that were asked in the parts of share of symptoms on SNSs, perceived value of SNSs, perceived psychological safety on SNSs, health search abilities, and the amount of health search. As a result of analysis, four factors accounted for 70.2% of the variance of the variables included in the analysis. Varimax rotation techniques was used and resulting loadings for each factor can be seen in the table below. The result suggested that the questions asked were consistent with their constructs except that perceived value and psychological safety fell into the same factor. This unexpected result might be caused due to our limited sample size and by the fact that they both have positive effect on symptom share.

Table 45: Result of Explanatory Factor Analysis

	Share of Symptoms on SNSs	Perceived Value and Psychological Safety	Health Search Abilities	The Amount of Health Search
Q2-1-Healthcare System Search				.685
Q2-2-Symptom Search				.778
Q2-3-Doctor Search				.741
Q2-4-Diagnosis Search				.859
Q2-5-Medicine Search				.806
Q2-6-Experienced People Search				.770
Q4-1 Reaching Information Sources			.843	
Q4-2 Distinguishing Valuable Information			.833	
Q4-3 Finding Comprehensive Information			.873	
Q4-4 Decision Making Based on Information Found			.893	
Q6-1 Express Myself Better		.801		
Q6-2 Look for Help		.635		
Q6-3 Feel Isolated in Absence		.685		
Q6-4 Important Part of My Life		.727		
Q6-5 Right Place to Share		.239		
Q6-6 Have Friends		.801		
Q6-7 Friends Share		.787		
Q6-8 Supportive Reaction		.822		
Q7-1-Happy	.774			
Q7-2-Betrayed	.543			
Q7-3-Everthing Will Be Bad	.627			
Q7-4-Peaceful	.721			
Q7-5-Health Concerns	.728			
Q7-6-Homework	.702			
Q7-7-Nervous	.663			
Q7-8-Self Confident	.683			
Q7-9-Angry	.680			
Q7-10-Treat Others Bad	.777			
Q7-11-Self Harm	.672			
Q7-12-Anxious	.640			
Q7-13-Traumatic	.692			
Q7-14-Headache	.761			
Q7-15-Scared	.653			
Q7-16-People Like Me	.756			
Q7-17-Bad Will Happen	.769			
Q7-18-Good Happens To Me	.717			
Q7-19-Feel Bad	.810			
Q7-20-People Treat Me Bad	.778			

Cronbach's Alpha

This study, which is based on measurement, must be concerned with the validity, dependability or reliability of measurement. A reliability coefficient shows whether the test designer was correct in expecting a certain collection of items to yield interpretable statements about individual differences (Kelley 1942). The validity measurement, factor analysis can not be explained without appropriate estimate of the magnitude of the error of measurement. Testing for internal consistency only requires the measurement procedure to be completed once during the course of the experiment, without the need for a pre- and post-test (Cronbach 1951). Single tests in non-experimental research; for instance, relationship-based research that have no intervention/treatment. The preferred way to find out how accurate single time measures are to make two independent measurements and compare them. In real life, social research area workers do not have regularly the opportunity to recapture their subjects for a second test. Clinical tests are generally worked into a busy schedule, and there is always a desire to give additional tests if any extra time becomes available (Salthouse and Hedden 2002). It is hard enough to schedule twenty tests for a factorial study, only scheduling another twenty just to determine reliability is not realistic. Therefore, the reliability of the measurement procedure has to be calculated internally when the measurement is completed once. This calculation basically evaluates the internal consistency of the different items that make up the measurement. Reliability as internal consistency can be determined using a number of methods. We looked at two methods as the split-half method and Cronbach's Alpha.

Split-half method assesses the reliability by splitting the measures from the measurement process in half, and then calculating individually the scores of each half. Method has several steps; first it must be decided how to divide the measures/items from the measurement process. After dividing the measures from the measurement process, the scores of each of the halves is calculated one by one. Later on internal consistency between the two sets of scores is examined, the measurement procedure is considered to show split-half reliability if the two sets of scores are highly correlated, for example: there is a strong relationship between the scores.

Cronbach's Alpha (α) is an estimate of the correlation between two random samples of items from a universe of items like those in the test. α is "found to be a suitable index of equivalence and, except for very short tests, of the first-factor concentration in the test" (Cronbach 1951). It is a function of the number of variables in a test, the average covariance between pairs, and the variance of the total score. It has been suggested that can be seen as the expected correlation of two tests that measure the same construct. By using this definition, it is implicitly assumed that the average correlation of a bunch of measures is an accurate estimate of the average correlation of all measure related to a known construct (Cronbach 1946). At the undergraduate and master's dissertation level, Cronbach's alpha is expected to be used instead of the split-half method. It is widely used in written/standardized tests. It provides a coefficient of among measures correlations, where a strong relationship between the measures within the measurement procedure suggests high internal consistency, generally Cronbach's alpha coefficient of 0.80. Cronbach's alpha is often used when one has multi-items scales. Cronbach's alpha is a sophisticated test of internal consistency because it can be used for attitudinal measurements, which are popular amongst researchers, such attitudinal tests include Likert scales with options from "strongly agree" to "strongly disagree".

In this study, Cronbach's alpha of each control variable with multiple question and construct in the conceptual model was calculated and the results can be seen in the table below. Only variables with a Cronbach's alpha value lower than 0.80 were the amount of internet use and the amount of SNSs use. These two variables are not expected to have internal consistency. For example, one does not expect high internet use through computer just because of high internet use through smart phone. Likewise, high Facebook activity does not require an expectation of high SnapChat activity.

Table 46: Cronbach's Alpha Coefficients of Each Variable

	Cronbach's Alpha
The Amount of Internet Use	0.165
The Amount of Health Search	0.962
Health Search Abilities	0.927
The Amount of SNSs Use	0.741
Perceived Value of SNSs	0.906
Perceived Psychological Safety on SNSs	0.816
Share of Symptoms on SNSs	0.977

Correlation Table

A correlation table was constructed for the control variables and constructs in our conceptual model. It can be seen in the table below.

Table 47: Correlation Table of The Control Variables and Constructs

	The Amount of Internet Use	The Amount of Health Search	Health Search Abilities	The Amount of SNSs Use	Perceived Value of SNSs	Perceived Psychological Safety on SNSs	Share of Symptoms on SNSs
The Amount of Internet Use	1	.325**	.346**	.503**	.434**	.382**	.399**
The Amount of Health Search	.325**	1	.846**	.223**	.128	.105	.168*
Health Search Abilities	.346**	.846**	1	.267**	.162*	.140*	.163*
The Amount of SNSs Use	.503**	.223**	.267**	1	.633**	.546**	.534**
Perceived Value of SNSs	.434**	.128	.162*	.633**	1	.903**	.854**
Perceived Psychological Safety on SNSs	.382**	.105	.140*	.546**	.903**	1	.812**
Share of Symptoms on SNSs	.399**	.168*	.163*	.534**	.854**	.812**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

4.6-Conceptual Model Testing

After presenting the measurement results and explanatory analysis of all the control variables and constructs in the conceptual model, our proposed hypothesis should be tested to see whether the survey results confirm the hypothesis and so the conceptual model. For the methodology of conceptual model testing, moderated linear regression analysis was adopted. Perceived value of SNSs was defined as independent variable and share of symptoms on SNSs were defined as dependent variable. Perceived psychological safety on SNSs, on the other hand, defined as the moderator on the relationship between perceived value and symptom share. To better understand the moderation effect, a hierarchical regression analysis was conducted with perceived value and psychological safety entered in the first block and the interaction term entered in the second block. Before running the analysis, the variables were centered around their respective means to avoid multi-collinearity as suggested by Cohen and colleagues (2003). Centering process was done by subtracting the mean of the variable from each score. The results of the analysis can be seen in the table below. Both constructs have significant positive effects on the dependent variable as can be seen from the result of the first block of the regression analysis. There is a significant R square change with the addition of interaction term to the model. This shows that there is a significant moderation effect of psychological safety on the relationship between the perceived value and symptom share.

Table 48: Results of Regressions for the Conceptual Model

	Model Summary							ANOVA					
	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	Sig. F Change		Sum of Squares	df	Mean Square	F	Sig.
Model 1: Perceived Value of SNSs and Perceived Psychological Safety on SNSs	.859	.738	.736	.5138	.738	311.842	.000	Regression	164.655	2	82.328	311.842	.000
								Residual	58.345	221	.264		
								Total	223.000	223			
Model 2: Interaction Term added	.867	.752	.748	.5016	.013	11.895	.001	Regression	167.648	3	55.883	222.108	.000
								Residual	55.352	220	.252		
								Total	223.000	223			

Table 49: Coefficients of The Regressions for The Conceptual Model

Coefficients						
		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
Model 1	(Constant)	1,24E-12	.034		.000	1.000
	Perceived Value of SNSs	.656	.080	.656	8.207	.000
	Perceived Psychological Safety on SNSs	.220	.080	.220	2.747	.007
Model 2	(Constant)	-.154	.056		-2.761	.006
	Perceived Value of SNSs	.579	.081	.579	7.132	.000
	Perceived Psychological Safety on SNSs	.226	.078	.226	2.900	.004
	Perceived Value * Per. Psycho. Safety	.172	.050	.136	3.449	.001

After hypothesis testing and having statistically significant confirmations of the hypothesis, the effects of control variables were examined. Another hierarchical regression analysis was conducted by entering diseases and demographic variables in the first block. The amount of internet use, the amount of health search, health search abilities, and the amount of SNSs use were entered in the second block of the hierarchical regression. Finally, perceived value of SNSs and psychological safety on SNSs and the moderation term were entered in the third block of the hierarchical regression analysis. The results and statistically significant control variables can be seen in the table below. Having MDD diagnosis, the amount of internet and SNSs uses had positive effects on share of symptoms on SNSs as expected from the literature. On the contrary, number of siblings had a negative effect on symptom shares. It can be explained by the typical case of having only one device for all siblings in a Turkish family.

Table 50: Effects of Control Variables on The Conceptual Model

	Model Summary							ANOVA					
	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	Sig. F Change		Sum of Squares	df	Mean Square	F	Sig.
Model 1: Diseases and Demographic Variables	.404	.163	.103	.9471	.163	2.708	.001	Regression	36.438	15	2.429	2.708	.001
								Residual	186.562	208	.897		
								Total	223.000	223			
Model 2: The Rest of Control Variables Added	.633	.401	.345	.8093	.237	20.206	.000	Regression	89.378	19	4.704	7.182	.000
								Residual	133.622	204	.655		
								Total	223.000	223			
Model 3: Perceived Value, Psychological Safety, and Interaction Term Added	887	.787	.764	.4857	.387	121.827	.000	Regression	175.588	22	7.981	33.836	.000
								Residual	47.412	201	.236		
								Total	223.000	223			

Table 51: Coefficients of Significant Control Variables

Significant Coefficients					
Control Variables	Unstandardized		Standardized	t	Sig.
	B	Std. Error	Beta		
Major Depressive Disorder	.514	.169	.257	3.043	.003
Number of Siblings	-.194	.090	-.248	-2.159	.032
The Amount of Internet Use	.166	.065	.169	2.530	.012
The Amount of SNSs Use	.256	.040	.423	6.417	.000

5-Discussion

Considering incredible proliferation of social networking sites and high use rate of SNSs among adolescents, there is a considerable amount of data about adolescents on these platforms. It is possible to develop a computer code that analyzes this data and provide valuable information to psychiatrists to support diagnosing and patient follow-up process. Although detecting psychiatric symptoms is technologically achievable; which percentage of adolescent shares which symptoms on SNSs is not studied in depth. The objective of this study is to examine under which conditions and how frequent patients share their symptoms on their SNSs profile.

In accordance with the objective, the hypotheses were developed based on theory and previous research. The perceived value of SNSs and psychological safety on SNSs were expected to increase symptom share on SNSs. Moreover, we expect psychological safety to moderate the relation between perceived value of SNSs and symptom share on SNSs.

As a result of survey application, 224 respondents' data were collected. Conceptual model was tested using moderated linear regression model and all the three hypotheses were statistically confirmed with the results of the survey.

People attribute varying values to SNSs in accordance with their personal preferences, the offers of SNSs, and the characteristics of their network in the SNSs. As a result of these drivers if an adolescent gives high importance to a specific SNS, she/he is likely to share psychological symptoms on that SNS. In a similar way, if the adolescent feels safe to disclose emotions on the SNS, chance of sharing psychological symptoms increases. Moreover, it found that feeling psychologically safe in an SNS moderates the effect of attributed value on symptom share. Some people might give high importance to an SNS and frequently use it. However, if they feel a threat to their psychological safety on the SNS, such as commercial use of their private information or privacy right abuses, then they choose not to share any feeling while intensively using different functions of the SNS. In another example, although people might trust an SNS company, they might have their professional colleagues on their network in the specific SNS. Therefore, this situation harms their psychological safety on the SNS if they feel that they will look weak against their professional colleagues when disclosing emotions. The findings from the analysis are inline with the literature as explained in the hypothesis development part of the report.

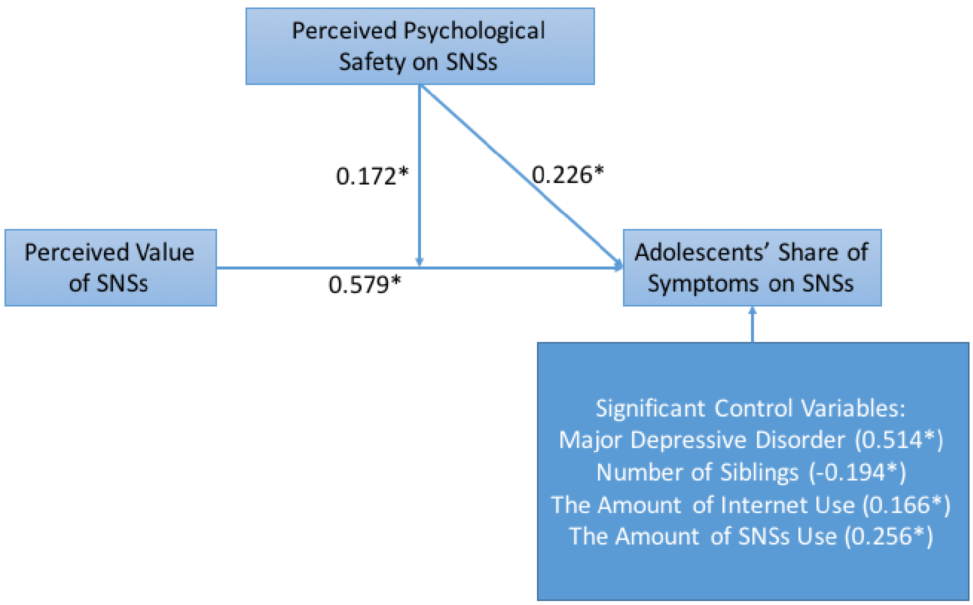

Figure 33: Result Summary of Conceptual Model Testing

As a result of control variables analysis, patients with major depressive disorder found to share more symptoms on SNSs as expected from the literature (Gürbüz 2015; Christofides et al. 2011; Chen and Lee 2013). The main symptoms of depression are persistent low mood, low self esteem, and loss of interest and pleasure. The SNSs users with these symptoms found to share their emotions with their network on SNSs more frequently than patients with other diseases.

Another significant control variable was number of siblings of respondents, which is explained by the typical situation in Turkey. Families with limited financial income cannot afford technological devices for every child in the family, especially when have a relatively high number of children. Thus, the parents often buy one device for all the children to use together. In Turkey, families with low income level tend to be less educated and so have less birth control awareness and family planning. Therefore, most low income families in Turkey have multiple children. The result of our survey study coincides with these facts of Turkey.

Although 40.7% of people in the world and 51% of people in Turkey have access to internet, the amount of time spent online varies depending on needs, abilities and societal factors (World Bank Group 2016). Adolescents are prone to use SNSs extensively when they have access. Most scholars agree that the amount of internet use increases the amount of SNSs use of adolescents. Both of the variables positively affect the share of symptoms on SNSs. (Christodies et al. 2011; Settanni and Marengo 2015; Singleton et al. 2016 Gurbuz 2015; Lin et al. 2014; Sinn and Syn 2013; Rosen et al. 2012; Frison and Eggermont 2014). When the the amount of internet and SNSs use controlled, they found to be statistically significant, inline with the literature.

In the study, the amount of health related online search and health search abilities were also measured. From the past research, the two variables were expected to positively affect symptom share on SNS (Hargittai 2001; Skinner et al. 2003; Sarasohn 2008; Nutbeam 2006; White and Dorman 2001; McMullan 2006). However, the result of our survey study indicated no significant of the two variable on adolescents' symptom share on SNSs.

Considering adolescents' share of symptoms on SNSs, it was observed that 72% of adolescents in our sample shared their psychological symptoms. It is a promising number for detecting psychiatric symptoms from SNSs data with purpose of supporting psychiatrists. Especially for patients with high perceived value and psychological safety on SNSs, the result of a psychiatric symptom detection software would be meaningful, objective, and valuable for diagnosis. In terms of different categories of symptoms, while depressive symptoms and traumatic events are the most shared category of symptoms, somatic complaints and self harm related symptoms remained the least shared symptoms by adolescents in our sample. Moreover, positive feelings, such as feeling happy and sharing of a good experience, were shared more frequently than negative feelings, such as sharing headache and self-harm. These findings were expected from the literature (Lin et al. 2014; Settanni and Marengo 2015; Denti et al. 2012).

Some of our other findings from the measured variables also provided useful hints and insights about the context. Adolescents with working mother were observed to use SNSs more. Education level of mother of an adolescent showed a significant effect on the adolescent's online health search amount and abilities. ADHD patients had low levels of health search activities and abilities as it can be explained by the very nature of their disease.

In this study, we contributed the literature by developing a relatively simple but explanatory model for adolescent's share of symptoms on SNSs. Our findings from the survey with a considerable sample size confirmed our hypotheses in the model developed. Even though larger sample size and more extensive studies are necessary to conclusively confirm our model, our study shed light on the causal mechanisms among adolescents' symptom share, perceived value of SNSs, and perceived psychological safety on SNSs. The model and the result of the survey imply that detecting adolescents' psychiatric symptoms from SNSs data is applicable. The existence of an opportunity of developing software with such objective makes further efforts worthwhile.

Limitations

In our study, we were able to collect 224 valid survey results in spite of our efforts to collect more. To be able to conclusively confirm our conceptual model, it is necessary to have a sample size that is large enough to at least conduct a confirmatory factor analysis. Also the survey was conducted in single location in Turkey, so it is difficult to say that our sample represent the whole Turkish population. Despite our efforts to statistically compare our sample with all the adolescents admitted to psychiatry clinics in Turkey, there was not any available data regarding the whole Turkish population. In addition, our target audience was Turkish people. In order to evaluate our model and extent our findings universally, confirmatory studies must be conducted in other parts of the world.

In the study, all measurements were conducted through the survey. Therefore, the source of measurement results related to all variables, especially the symptom share, was the respondents of the survey. Although there is not an expected bias, such as social desirability or other forms of CMV, analysis of adolescents SNSs' profiles would provide a more objective and detailed results. This would also reduce the time necessary to fill our questionnaire, which was 20 minutes, relatively long for a survey study. Time consuming questionnaires might give missing results, especially from the respondents with ADHD, as it was the case in our study.

Cross sectional nature of this study was another limitation. Collecting data from the respondents at a single point in time restricts understanding the causal relations between variables and observing the changes in variables with time. A longitudinal data collection from respondents would address these issues.

As our study implied, the content analysis software that can detect psychiatry symptoms from SNSs data can be developed. The software should be tried with numerous patients, as well as healthy adolescents as a control group, from all around the world. With the results of these trials, correlations between scores for different symptoms obtained from the software and diseases diagnosed by psychiatrists must be revealed and then calibration of the software must be done.

6-Conclusion

With the rapid spread of SNSs across ages and cultures and advance of big data technologies, the data generated by people and stored on SNSs create great opportunities for all sectors including healthcare. Increasing importance of child and adolescent psychiatry for people's life to be healthy requires to capture these opportunities. Therefore, it is needed to further study SNSs data in relation with child and adolescent psychiatry.

Within this direction, we proposed a model explaining causal relations of adolescents' symptom shares on SNSs with the perceived value and psychological safety. Then, we conducted a survey with 224 adolescents who admitted to a psychiatry clinic in Turkey. The results of the survey supported the model.

The findings suggested that adolescent would share their symptoms on SNSs only if they attribute value to the SNSs that they use. Feeling psychologically safe in SNSs also directly affects their symptom share and indirectly moderates how much they share symptoms for a given perceived value. Moreover, a majority of adolescents in our sample shared their symptoms on SNSs. Hence, there is an attractive opportunity for the development of a software program for detecting symptoms to support psychiatrist in their diagnosis.

7-Appendix

7.1-Demography Test

1.Gender: (   )Female   (   )Male
2.Birth Date: ……./………/……
3.Are your mother and father married?
( ) yes ( ) divorced ( ) father not present ( ) mother not present
4. What is your mother's age? ……
5. What is your father's age? ……
6. Mother's education level:
(   ) Never went to school   (   )Primary school (   )Middle School   (   )High School
(   )University
7. Father's education level:
(   ) Never went to school   (   )Primary school (   )Middle School   (   )High School
(   )University
8. Mother's job:
(   ) Not employed (   )Full-time employed (   ) Retired
9. Father's job:
(   ) Not employed (   )Full-time employed (   ) Retired
10. Average monthly family income:
( ) 1000 tl or less   ( ) 1000-3300tl ( ) 3300 tl or more
11. Please select all who live with you.
My birth mother (   )   My birth father (   ) My step-mother (   )
My step-father (   )   others(   )
12. How many siblings do you have?
(   ) **1**   (   ) **2**   (   ) **3**   (   ) **4**   (   ) **5 or more**
13. Please mark your birth order.
(   ) First   (   ) Second   (   ) Third   (   ) Forth   (   ) Fifth or more
14. Do you have a chronic disease like diabetes, hypertension, heart diseases, cancer, epilepsy, asthma or anemia? Please explain.
(   ) **Yes, I have .**……………………   (   ) **No, I do not.**
15. Do you have a psychiatric disease diagnosed by a specialist doctor? Please explain.
(   ) **Yes, I have .**……………………   (   ) **No, I do not.**

7.2-Internet and Social Media Usage Questionnaire

1. From which channels do you use the Internet? How frequently do you use the Internet?

	> 6 hours daily	4-5 hours daily	1-3 hours daily	< 1 hour daily	< 5 hours weekly	Never
Computer (PC)	☐	☐	☐	☐	☐	☐
Smart Phone	☐	☐	☐	☐	☐	☐
Tablet	☐	☐	☐	☐	☐	☐

2. Do you use the Internet to search for information about your health, hospitals, or healthcare systems? Which search engines and websites do you prefer? In the last year, did you create any content related to any of the following topics: sharing pictures, video, or other online content?

Please Start Here	Have you done any online search in the last year?					If you searched / Which websites?											
	No, not interested	No, but interested	Yes			Official Websites			Online encyclopedias (Wikipedia)			Blogs and forums			Social media websites		
			Rarely	Sometimes	Frequently	Rarely	Sometimes	Frequently	Rarely	Sometimes	Frequently	Rarely	Sometimes	Frequently	Rarely	Sometimes	Frequently
Healthcare systems, hospitals, departments, services, contact information, working hours, etc.	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Concerns and symptoms before seeing a doctor	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Reviews for doctors, information about different health care professionals	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
New or potential medical diagnosis and treatments	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Prescribed medicines and side effects	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
To find people with similar conditions and to learn about their experiences	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

3. In the last year, did you create any content related to health? Did you share pictures, videos, your research or any other online content? Did you comment on health related contents? How Frequently?

	Blogs and forums			Social media websites		
	Never	Sometimes	Frequently	Never	Sometimes	Frequently
I share my concerns about my health.	☐	☐	☐	☐	☐	☐
I share my experiences about the doctor and the hospital during my visit.	☐	☐	☐	☐	☐	☐
I share my diagnosis.	☐	☐	☐	☐	☐	☐
I share my prescribed medicine and treatments.	☐	☐	☐	☐	☐	☐
I share the side effects of the medicines that I used.	☐	☐	☐	☐	☐	☐
I share the treatment process and outcomes.	☐	☐	☐	☐	☐	☐

4. Please read the sentences below and mark between 1 and 7 indicating if you agree or disagree.

- : Not applicable
1: Strongly Disagree
2: Disagree
3: Partially Disagree
4: Neutral
5: Partially Agree
6: Agree
7: Strongly Agree

	-	1	2	3	4	5	6	7
I know how to reach information about my health online.	☐	☐	☐	☐	☐	☐	☐	☐
I can distinguish valuable resources from unreliable online health resources.	☐	☐	☐	☐	☐	☐	☐	☐
I can reach comprehensive information on the internet.	☐	☐	☐	☐	☐	☐	☐	☐
I feel secure in making decisions about my health based on the information found online.	☐	☐	☐	☐	☐	☐	☐	☐

5. Please mark how frequently you use the following social media websites.

	> 6 hours daily	4-5 hours daily	1-3 hours daily	< 1 hour daily	< 5 hours weekly	Never
Facebook	☐	☐	☐	☐	☐	☐
Instagram	☐	☐	☐	☐	☐	☐
Twitter	☐	☐	☐	☐	☐	☐
Snapchat	☐	☐	☐	☐	☐	☐
Google+	☐	☐	☐	☐	☐	☐
Onediyo.com	☐	☐	☐	☐	☐	☐
Vine	☐	☐	☐	☐	☐	☐
Pinterest	☐	☐	☐	☐	☐	☐
Scorp	☐	☐	☐	☐	☐	☐
Tumblr	☐	☐	☐	☐	☐	☐
Ask.fm	☐	☐	☐	☐	☐	☐

Which one do you use most? ……………………………

6- Please read the sentences below and mark between 1 and 7 indicating if you agree or disagree

- : Not applicable
1: Strongly Disagree
2: Disagree
3: Partially Disagree
4: Neutral
5: Partially Agree
6: Agree
7: Strongly Agree

	-	1	2	3	4	5	6	7
I feel more relaxed (express myself better) on social media website than I do in my daily life (school, home etc.).	☐	☐	☐	☐	☐	☐	☐	☐
When I have emotional and psychological problems, I look for help on social media websites.	☐	☐	☐	☐	☐	☐	☐	☐
I feel isolated when I do not have access to social media websites.	☐	☐	☐	☐	☐	☐	☐	☐
Social media websites are an important part of my life.	☐	☐	☐	☐	☐	☐	☐	☐
Social media websites are not the right place to share my feelings honestly and openly.	☐	☐	☐	☐	☐	☐	☐	☐
On social media websites, I have friends that I can share my problems and concerns.	☐	☐	☐	☐	☐	☐	☐	☐
On social media websites, many of my friends frequently share their feelings openly.	☐	☐	☐	☐	☐	☐	☐	☐
When I share my feeling on social media websites, I mostly receive supportive reactions from my friends	☐	☐	☐	☐	☐	☐	☐	☐

7. If you were in any of the following situations, would you do anything on social media websites? What would you do? How frequently?

	I talk to my friends online			I update my status			I change my profile photo			I share a photo related to my feelings			I share a video related to my feelings			I share a song related to my feelings			I comment on my friends' posts			I do not do anything
	Rarely	Sometimes	Frequently	Rarely	Sometimes	Frequently	Rarely	Sometimes	Frequently	Rarely	Sometimes	Frequently	Rarely	Sometimes	Frequently	Rarely	Sometimes	Frequently	Rarely	Sometimes	Frequently	
When I feel happy …	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
When I feel betrayed…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
When I feel like everything will be bad…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
When I feel peaceful and comfortable…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
When I have concerns about my health…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
When I have homework or an assignment to finish…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
When I feel nervous…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
When I have high self-confidence…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
When I feel angry…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
When I think I treat others badly…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
When I think of harming myself…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
When I feel anxious…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
When I go through a traumatic event…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
When I have headache, stomachache, or nausea…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
When I am scared…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
When I feel people like me…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
When I feel like something bad will happen…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
When something really good happens to me…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
When I feel bad…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
When I think that people treat me poorly…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

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