YANGON UNIVERSITY OF ECONOMICS

DEPARTMENT OF STATISTICS

SOCIAL MEDIA IMPACT ON STUDENTS IN BAGO UNIVERSITY

SWE SWE WIN HTET

M. Econ (Statistics)

Roll No. 4

December, 2018

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ABSTRACT

Social media has penetrated to the many areas in daily lives of students. The main objective of the study is to investigate the causes and effects of social media that impact on students according to the basic of a sample survey that was carried out in June 2018. A sample of students falling within the age group 16-24 was selected by using the stratified random sampling. In this study, it found that the mutual relationship between social media and students was highly significant. Factor analysis has been applied to explore that the significant factors of social media impact on students. Moreover, confirmatory factor analysis has also been applied to determine that the relationship and interactive structure between the effect and usage of social media in students. It was found that there was a causal relationship between social media actual usages and various effects of social media. Also, the students used social media for learning utilization, personal and multiple usages. Students were getting bored of their study, conflict within family and facilitate laziness because of social media. Moreover, social media usages appeared the personal problem, physical problem and mind problem in students. It was found that social media usage for learning utilization and multiple uses, addiction of social media usages and usable place for social media are difference between male and female students.

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LIST OF ABBREVIATIONS

BBC	=	British Broadcasting Corporation
BSD	=	Berkeley Software Distribution
CFA	=	Confirmatory Factor Analysis
CFI	=	Comparative Fit Index
EFA	=	Exploratory Factor Analysis
EPF	=	Employees Provident Fund
FML	=	Fit of Maximum Likelihood
GFI	=	Goodness of Fit Index
GK	=	Global Kapital Group
IP	=	Internet Protocol
IRT	=	Interactive Response Technology
KMO	=	Kasier Meyer Olkin
LAN	=	Local Area Network
LLC	=	Limited Liability Company
MAB	=	Multi-author Blog
ML	=	Maximum Likelihood
NCP	=	Non Centrality Parameter
RMR	=	Root Mean Square Error
RMSEA	=	Root Mean Square Error of Approximation
SE	=	Standard Error
SIM	=	Subscriber Identification Module
SMS	=	Short Message Service
SRMR	=	Standardized Root Mean Square Residual
SQRT	=	Square Root
URL	=	Uniform Resource Locator

CHAPTER I

INTRODUCTION

1.1 Rationale of the Study

Today's world is a global village. Everyone is connected to one another in the vast network generated by the Internet. Internet technologies have a growing usage level day by day. The Internet in Myanmar has been available since 2000 when the first Internet connections were established. Myanmar is becoming an emerging and fast developing Internet usage in South East Asia. Beginning in 2011, the pervasive levels of Internet censorship were significantly reduced. According to World Internet Statistics in2012, Myanmar had over 534,930 Internet users (1.0% of the population) due to government restrictions on pricing and deliberate lack of facilities and infrastructure. In 2013, only around 10 percent of the population had access to a phone.

In 2014, the price of SIM cards is decreasing with the growth of Internet use in Myanmar and opening of telecommunications. Mobile and Internet penetration has significantly increased. In 2015, the internet users significantly increased to 12.6% with the introduction of faster mobile 3G internet by transnational telecommunication companies. In 2016, the government estimated that 75 percent of the population will have access to mobile phones and around 60 percent of Myanmar's population uses Facebook or other forms of social media. There has been an overall growth of Internet users of Myanmar and at 90 percent of adults used social media such as Facebook, Google, YouTube and so on.

Today, the number of Facebook user is 91.3% of Internet user and YouTube, Google, Twitter, Instagram, and Viber are the mostly useful social platforms in Myanmar. Many people spend about 40% of their time online using social media, playing games, for academia, for business, for personalities and so on. Social media is becoming an integral part of life online as social websites and applications proliferate. Increasing social media usage level gives opportunity for new software developments and making investments in this area. Thus, social media has not only economic function but also make persons participate in social life. Furthermore, it also provides opportunities for undemocratic actions and operations as in terms of democratic society life. Identifying users' habits has an important function on determining economic, social and cultural effects of social media. The most of people use social networking to stay connected, make friends and satisfy their social needs.

The most important things in a student's life are studying, learning good habits and gaining knowledge to become a person with moral character. Today, this optimal learning process is seriously jeopardized by students becoming entrapped by the ploys of social networking. Social media and social networking usage are an increasing trend among students in all around the world. The use of social media in education provides students with the ability to get more useful information, to connect with learning groups and other educational systems that make education convenient. Social network tools afford students and institutions with multiple opportunities to improve learning methods. Students access and use social media mostly with using their smart phones.

Top reasons of students' social media usage are sharing document, information and opinion and entertainment. Students neglect their studies by spending time on social networking websites rather than studying or interacting with people in person. Actively and frequently participating in social networking can negatively affect their grades or hamper their journeys to their future careers. They like to make new friends and comment on the lives of different people. Students can create other online identities that the real world does not allow. Consistently thinking in this way can sometimes lead to depression. Social media appear many physical, mind and health problem. Social media can be used any time in daily that appear poor eyesight, tension on tendons and muscles, stress and depression. Most of students use social media with mobile. Students have more expenses because of mobile phone bill. If other devices have used, they more expend in internet and wifi bill. In recent years, social media and social networking usage are rapidly increasing in Myanmar. According to these situations, the attitudes, impact and behaviors of social media usage among university students have been studied and analyzed with the statistical techniques such as multivariate techniques in this study.

1.2 Objective of the Study

The main objective of this study is to study the relationship between social media and students in BAGO University. The specific objectives of this study are

(i) To explore the purpose of using social media in university students.

(ii) To examine the factors related to social media impact on university students.

(iii) To analyze the interaction between actual usages and social media impact on university students.

1.3 Scope and Limitations of the Study

Social media can be used many aspects of people and the various aspects of social media impact on society. Among them, social media usage impact on university students that have been analyzed by the primary data. Also, a sample survey was conducted in BAGO University. Data from personal interviews were analyzed to determine what factors related to social media usage and the causes and effects of social media impact on students.

1.4 Method of Study

In this study, 550 sample students within the aged 16-24 were selected from BAGO University's students. The design of the survey had been based on stratified random sampling. The questionnaire includes a total of 40 items and utilized a 5-point likert type scale. Descriptive Analysis, Exploratory Factor Analysis, Confirmatory Factor Analysis and Independent Sample test have been applied to assess the causes and effects of social media usages in this study.

1.5 Organization of the Study

This study consists of five chapters. Chapter I is the introduction chapter and it describes outlines rationale, objective, scope and limitation and method of the study. Chapter II has been presented the related literature review which includes social media, website and blog, type of social media and social media uses, impact on society and students. Chapter III covers the theoretical background which has been described Exploratory Factor Analysis, Confirmatory Factor Analysis and Independent Sample test. Chapter IV has been discussed Reliability Analysis of the Selected Factors, the Exploratory Factor Analysis for social media usage and Confirmatory Factor Analysis of the model. Chapter V contains findings and conclusions of this study.

CHAPTER II

OVERVIEW OF SOCIAL MEDIA

2.1 Social Media

Social media (also social networking service or site) is defined as internet-based technologies or online platforms that facilitate the building of virtual networks and communities and the sharing of ideas and information. Social media allows people to build social network or social relation with other people around the world. Social media is perceived as a Web 2.0 development that is the concept of a user-driven, interactive web. In 1997, the first recognizable social media site, Six Degrees was created. It enabled users to upload a profile and make friends with other users. Typically, people access social media services via web-based software on computer and laptops or web application on smartphones and tablets. Social media includes websites, blogs, message boards and chat rooms. Social media is used for social purposes, business purposes and education purposes. Depending on the social media platform, people may be able to contact and interact with any other people. Social networking sites provide people who develop their interests and find other people who share the same interests. All of social media sites have the common features that are user accounts, profile pages, friends, followers, groups, news feeds, personalization, notifications, information updating, saving and postings, digital photos, digital videos and links sharing and updating, like buttons and comment sections and review, rating or voting systems.

2.2 Internet

Internet is described as the global system of interconnected computer networks that use the Internet protocol suite (TCP/IP) to link devices worldwide. It is a network that consists of private, public, academic, business, and government networks of local to global scope, linked by a broad array of electronic, wireless, and optical networking technologies. The origins of Internet such as CompuServe were developed in the 1960. In 1980, the Internet was widely used by academia. The Internet carries a vast range of information resources and services such as the inter-linked hypertext documents and applications of the World Wide Web (WWW), electronic mail, telephony, and file sharing. The Internet redefine and reshaped most traditional communications media, including telephony, radio, television, paper mail and newspapers such as email, Internet telephony, Internet television, online music, digital newspapers, and video streaming websites. Book and other print publishing are adapting to website technology, or are reshaped into blogging, web feeds and online news aggregators. The Internet has enabled and accelerated new forms of personal interactions through instant messaging, Internet forums, and social networking.

2.3 Website

A website is a collection of related web pages (a document that is suitable for the World Wide Web and web browsers), including multimedia content (content that uses a combination of different content forms such as text, audio, images, animations, video and interactive content), typically identified with a common domain name (an identification string that defines a realm of administrative autonomy, authority or control within the Internet) , and published on at least one web server. A website may be accessible via a public Internet Protocol (IP) network or a private local area network (LAN), by referencing a uniform resource locator (URL) that identifies the site. The World Wide Web (WWW) was created in 1990 by the British CERN physicist Tim Berners-Lee. In 1993, the World Wide Web would be free to use for anyone. Websites have many functions and features and can be used in various aspects. A website can be a personal website, a commercial website, a government website or a non-profit organization website. Websites can be the work of an individual, a business or other organization, and are typically dedicated to a particular topic or purpose. Web pages can be viewed or otherwise accessed from a range of computer-based and Internet-enabled devices of various sizes, including desktop computers, laptops, tablet, computers and smartphones. The Web is a global set of documents, images and other resources, logically interrelated by hyperlinks and referenced with Uniform Resource Identifiers (URIs) that symbolically identify services, servers, and other databases, and the documents and resources that they can provide. World Wide Web browser software are Microsoft's Internet Explorer/Edge, Mozilla Firefox, Opera, Apple's Safari, and Google Chrome.

2.4 Blog

A blog (also weblog)is a discussion or informational website published on the World Wide Web. The term "weblog" was coined by Jorn Barger on 17 December 1997. The short form, "blog", was coined by Peter Merholz. Until 2009, blogs were usually the work of a single individual, occasionally of a small group, and often covered a single subject or topic. In the 2010s, multi-author blogs (MABs) have developed with posts written by large numbers of authors and professionally edited. Blog can also be used as a verb, meaning to maintain or add content to a blog. Blog can be seen as a form of social networking service. Many blogs provide commentary on a particular subject or topic, ranging from politics to sports. Others function as more personal online diaries, and others function more as online brand advertising of a particular individual or company. A typical blog combines text, digital images, and links to other blogs, web pages, and other media related to its topic. The ability of readers to leave publicly viewable comments, and interact with other comments, is an important contribution to the popularity of many blogs. There are many different types of blogs, differing not only in the type of content, but also in the way that content is delivered or written. They are personal blogs, collaborative blogs or group blogs, aggregated blogs, corporate and organizational blogs and micro-blogging.

2.5 Types of Social Media

There are the various types of social media in the world. Social media application and software develop in daily. The various social media are increasing day by day. The most of popular and usage of social are presented.

Facebook

Facebook is a popular free social networking website that allows registered users to create profiles, upload photos and videos, send messages and keep in touch with friends, family and colleagues. Facebook was originally intended for college students, but now anyone can join the network. Its purpose is to give people a way to share information in an easy and entertaining way. This site is available in 37 different languages and includes public features such as

Marketplace- Facebook allows members to post, read and respond to classified advertisements.

Groups -Facebook allows members who have common interests to find each other and interests.

Events- Facebook allows members to publicize an event, invite guests and track who plans to attend.

Pages - Facebook allows members to create and promote a public page built around a specific topic.

Presence technology - Facebook allows members to see which contacts are online and chat.

Facebook Messenger

Facebook Messenger (sometimes known as Messenger) is a messaging app and platform. Originally developed as Facebook Chat in 2008 and subsequently released standalone iOS and Android apps in 2011. People can send messages and exchange photos, videos, stickers, audio, and files, as well as react to other people' messages and interact with bots. The service also supports voice and video calling.

Twitter

Twitter is a social networking and free micro blogging service that allows registered members to send and receive text-based messages or broadcast short posts called tweets. Twitter members can broadcast tweets and follow other users by using multiple platforms and devices such as computers and smart phones, and can view tweets posted by other followed users. Twitter is also referred to as the SMS of the Internet because of it unmatched popularity and similarly the SMS text messaging system used on smartphones. Sometimes, twitter is called the social media television because it can inform people about various TV events such as the Oscars, MTV Video Music Awards and so on.

Google

Google (also Google search) is an Internet search engine and the top search engine in the world. It is designed to retrieve and order search results to provide the most relevant and dependable sources of data possible. Google's stated mission is to organize the world's information and make it universally accessible and useful. Google began in January 1996 as a research project by Larry Page and Sergey Brin. Google can be categorized many branches such as Google + (social networking), Google chrome (web browser) and YouTube (video sharing).

Google +

Google + (Google plus) is Google's social networking project and designed to replicate the way people interact offline more closely than is the case in other social networking services. The project's slogan is "Real-life sharing rethought for the web".

Google+ is launched Google LLC in June 2011. Features included the ability to post photos and status updates to the interest-based communities, group different types of relationships, a multi-person instant messaging, text and video chat, events, location tagging and the ability to edit and upload photos to private cloud-based albums.

Google Chrome

Google Chrome (commonly known simply as Chrome) is a freeware web browser developed by Google LLC. In 2008, it was first released for Microsoft Windows, and was later ported to Linux, macOS, iOS and Android. Google Chrome is also the main component of Chrome OS, where it serves as a platform for running web apps. Google Chrome features a minimalistic user interface, with its user-interface principles later being implemented into other browsers. Chrome also has a reputation for strong browsers performance.

YouTube

YouTube is a video-sharing website and was created the service in 2005. Google LLC bought the site in 2006.YouTube allows users to upload, view, rate, share, add to favorites, report, comment on videos, and subscribe to other users. It offers a wide variety of user-generated and corporate media videos. Available content includes video clips, TV show clips, music videos, short and documentary films, audio recordings, movie trailers, live streams, and other content such as video blogging, short original videos, and educational videos. Most of the content on YouTube is uploaded by individuals, but media corporations, like the BBC, offer some of their material via YouTube as part of the YouTube partnership program. The vast majority of its videos are free to view, but there are exceptions, including subscription-based premium channels, film rentals, as well as YouTube Premium, a subscription service offering ad-free access to the website and access to exclusive content made in partnership with existing users.

Email

Electronic mail (email or e-mail) is a method of exchanging messages (mail) between people using electronic devices. Invented by Ray Tomlinson, email first entered limited use in the 1960s and by the mid-1970s had taken the form now recognized as email. Email operates across computer networks, which today is primarily the Internet. Some early email systems required the author and the recipient to be online at the same time, in common with instant messaging. Today's email systems are based on a store-and-forward model. Email servers accept, forward, deliver, and store messages. Neither the users nor their computers are required to be online simultaneously; they need to connect only briefly, typically to a mail server or a webmail interface, for as long as it takes to send or receive messages.

Viber

Viber is a cross-platform instant messaging and voice over Internet Protocol(IP) application operated by Japanese multinational company Rakuten and provided as freeware for the Microsoft Windows, macOS, Linux, Android and iOS platforms. It requires a telephone number to operate. In addition to instant messaging it allows users to exchange media such as images and video records.

2.6 Uses of Social Media

Practically social media is building more powerful around the world. In many countries, over half of the population uses social media and their applications, software and devices are growing rapidly. There are lots of positive and negative uses of social media in daily life. The positive uses can lead people to productive use of time, peace of mind and happiness, healthy conversations in which people like and enjoy by sharing personal and professional activities with a wide variety of people, groups, and communities. The negative uses of social media start when people don't have an alternative to spending time. When people are bored with work when students are bored with the study and they feel low or even highly confident, they go on social media.

Productive uses of social media

If people want to gain the advantages of social media websites and application in their daily life then they first need to understand clearly about the productive uses of social media. When people congregate and interact on a social platform, the productive uses of social media can be seen when they share and exchange content that has common values and goals with each other. It means that people build strong communities and units that enable them in future to get together and fight for a cause.

Use of social media for teachers

Teachers and educators can be the most impactful users of social media websites. They can use it to explore educational content, create multimedia presentations, 3D animations and so on, and to explain concepts of science and mathematics in a better way. They can create and write a meaningful post that able people to think and act generously. They can come rounds their opinions, minds, knowledge, and cooperate with students and other teachers.

Use of social media for students

The most addicted and attracted people or targeted people by social media websites and applications are students. Because they spend more time online, they share a variety of content and they are chatting and social things more than others. Reportedly, most teens spend an average of 8 hours per day online on social media. More than half of the population is addicted to social media it is very beneficial for social media companies and also good for users in some cases. It was meant to increase the social development. But the problem arises when people forget about their own personal development and spend that part of the time on social media.

Now the uses of social media for students should be for personal development and learning. Students can build communities and groups with a variety of educational concepts such as GK groups, study group, creative groups, anti-cyber bullying group, sharing their art etc. But the problem is that these things are done by companies and businesses instead of students. If students actually participate in such groups, that will be also helpful.

Use of social media for small businesses

One of the more prominent users of social media is small businesses and small business owners. It's because small business owners are the customers of social media websites. Social Media websites are used by small business owners to market their business to the targeted demographic by type of audience, location, age group etc. Today, social media websites are in existence due to the advertising potential and higher conversion rate offered by them for business owners. Almost all kind of businesses can be promoted that how these products and services are being hawked by social media platforms. Some social media websites such as Facebook are even providing an option to blog, promote and boost sales. The use of social media for marketing is increasing the income of social media websites and apps and that will enable to innovate. And their innovation means how they will be able to attract more users when they will be able to provide options and features so that users keep connected to social media channels.

Use of social media for digital marketing companies

The use of social media for digital marketing companies is similar to small businesses. Even digital marketing companies provide social media marketing services for small business owners. In this process, digital media marketing companies create viral content. Viral content on current causes that the entire community and people are engaged. Sometimes they create funny content, another day they create inspirational content and so on. And in middle of all this content bombardment, they promote the business content to them. Many digital marketer and companies create spam groups and communities to collect user's information to target for cold calling. It is just another way for them to exploit the large number of gullible social media users who don't mind giving out their phone number and email address for a free pen drive 'lucky draw' contest.

Use of social media for drivers

Drivers visit thousands of locations in a year repetitively. They visit holy places, mountains, and most dangerous roads. They also want to use Facebook, Google, and other social applications. They spend their remaining time on social media by sharing locations and beauty of nature with the people. And they can create community and groups around their passion. Later they can turn it into a passive income source.

Use of social media for data analysis expert

Social media is a top platform for market research and decision-making process. Billions of people use social media for learning, marketing, shopping and decision making. Now when they use social media, they create and generate data that enables data analysts to do the analysis on the related subject such as data about latest marketing campaigns and shared content. When this data is processed along certain parameters, it gives the valuable information that helps companies and corporations take key decisions regarding their business interests for the future.

Use of social media for government

There are thousands of government departments in any country such as forest department, income tax and sales tax department, EPF (Employees Provident Fund) department, transportation department, consumers, RTI (Right to Information) and many others. These units of government can use social media to make users aware and educated about their and own rights and the facilities provided by these units. They have staff and they can train them to use Facebook, Google and others to share the latest development and features of the citizen services. It is a great practice for the unity of the country and public development. The use of social networking or social media apps is nothing if it's not helping people or not enabling social development.

Use of social media politicians

Everyone knows that politicians use social media to test the waters of public opinion on certain topic and causes. They use it to connect with people. They use to make people aware and educated about the services and importance of the campaign. They hire digital marketing companies and marketers or ghost bloggers. One way or another, social media has become the nerve center around which election and poll-related strategies are formed and executed.

Use of social media for news media

The role of news media in the development of the country is bigger than others. News media gets almost 70% user attention on social media. There are 1000 of news websites you can see on social media and everyone is trying to get the attention. Everyone is trying to educate and driving traffic to their websites on even cheap and lowest quality post. But that's how they do it and this how this business works. They should aim for honest and meaningful content that is meant to educate the masses not divide them.

2.7 Impact of the Social Media on Society

Now social media has become an extremely popular online platform and an important part of life in the society. Social media impact on society is making economic, social and political changes around the globe. Social media has connected many different kinds of society that is communication, interactions and creating relationships with each other. Social media remove the geographical barriers between people and society is getting inspired by each other. Social media is improving human capacities and increasing in creativity after interacting with other. Social media provides anyone such as artists, writers, designers, programmers, students, job seekers, small business owners and other.

Social media offers audience and subject monitoring tools that are useful and it is one of the best platforms to extract data. People can easily find out any topic and specific issues from social media such as educational information and knowledge, business information, health and medical knowledge, beauty and fashion information, the world newsflash and articles news and organizational information and knowledge and ism, admonishment and liters and so on.

Social media provided freedom of options to share feelings and thoughts within society. It can be shared posts, video, photos and other just in span of minutes. Social media is increasing the living standard of society. Online shopping, online jobs, online marketing, online banking, online teaching and other online services are easily achieved on the social media. With social media people can communicate with anyone from anywhere at any time. Social media include many features, including long distance calls, video calls, and a certain number of free text messages, emotional sticker, photo, videos and voice mails sending. Social media has increased the rate and quality of collaboration for people. They are better able to communicate meeting times or share information quickly, which can increase productivity and help them learn how to work well in group.

Actions, thoughts, communication and information on the social media are actually impacting society positively or negatively. People are difficult their normal life without making use of social media. People have no interest in their environment, family, friends, education and jobs. Most of people are speaking and care about their friends from social media and they do not care about neighbors. They waste their time because they are busy chatting and using social media. Social troubles have occurred in their environments.

The use of computers, mobile phones, laptop and various gadgets to access social media may harm if people use it for long hours frequently. People may be exposed to bad posture, eye strain, physical and mental stress. Too much use of technology tools for accessing social media is harmful and there must be a limit.

2.8 Impact of Social Media on Students

Social media teaches and improves student's skills and abilities. Practices of social media increase student's social intelligence and understanding of human behaviors. By spending so much time working with new technologies, students develop more familiarity with computers and other electronic devices. With the increased focus on technology in education and business, this will help students build skills that will aid them throughout their lives. This can help students compile and produce useful content for search. Whether students are working on an assignment, working project or trying to gain more insight on a subject, some of the best information and results can be extracted from social media. Social media can help students build a portfolio for their career and can be used to start sharing work while a student is still in the learning space. Some of the ways social media can be used to create high levels of engaging, explore the possibilities of collaborative learning environments and enjoy the measurably positive effects on the teaching and learning process.

Students are more willing to connect when they can utilize technology to research information and share ideas. The use of social media tools helps students share information, communicate ideas and enhance their learning and demonstrate their mastery of content and skills. Designing lessons that ask students to utilize social media as they work to solve problems, complete projects and communicate ideas builds confidence, generates enthusiasm, and fosters a sense of play in the learning process. Students can get to know each other better through social media networks. It helps to bring together two or more people, where they can share their problem, which it can get solve by their fellow colleagues. If a student's finds out that he or she is having a problem in a particular course, he or she can open through chat and finds a genius who can provide a solution to the problem.

Many students find it difficult to go about their normal life without making use of social media. It has been observed that student does not interest and listen in class and they are busy chatting and only interesting on social media. They waste their time chatting with friends and family, instead of reading and practicing what they have learned in school. Increasing of social media usage arise them materialistic, angry and addicted to too many bad things. Social media has created many social problems between students. Todays, many students tend to choose online communication rather than having real time conversation, and this lead to students becoming an introvert. Many students stick to their gadget without concentrating on their study. It is a bad idea to waste away judicious time on social media platforms without gaining anything from it. Students should not be carried away by social media platforms because it will affect their academic performance.

The number of social media usages among students increases rapidly and they feel various health problem such as poor eyesight, neck pain and damage, head pain, arm pain and decreasing in brain activity, deprivation. Long-term usage leads to addition tension on tendons, muscles, and perimetric tissue. In addition, most of students use social media with mobile phones. Mobile phones emit radiofrequency energy which can enhance the health problem. Therefore, social media usages are really important for students and they should use social media to get the benefits of communication and technologies for their career, personal development and low effect of health problem.

CHAPTER III

RESEARCH METHODOLOGY

In this chapter, the theoretical background of the statistical techniques such as Reliability Analysis, Exploratory Factor Analysis, Confirmatory Factor Analysis and Independent Sample Test are presented.

3.1 Reliability Analysis

The reliability analysis of a measurement instrument is defined as the ability of the instrument to measure consistently the phenomenon it is designed to assess. Reliability refers to test consistency. The important of reliability lies in the fact that it is a prerequisite for the validity of a test. Simply, for the validity of a measuring instrument that does not reflect some attribute consistently has little chance of being considered a valid measure of that attribute. The internal consistency method is to determine the reliability of a measuring instrument.

Internal consistency refers to the extent to which the items in a test measure the same construct. Examining the internal consistency of the test enables to determine which items are not consistent with the test in measuring the phenomenon under investigation. The object is to remove the inconsistent items and improve the internal consistency of the test. An internally consistent test increases the chances of the test being reliable. The method of ascertaining the reliability of a test is Cronbach's alpha. Cronbach's alpha is a single correlation coefficient that is an estimate of the average of all the correlation coefficients of the items within a test. Mohd Salleh Abu (1958) and Zaidatun Tasir (1972) stated that if alpha is high (0.6 or higher), then this suggests that all of the items are reliable and the entire test is internally consistent. If alpha is low (0.3 or lower), then at least one of items is unreliable, and must be identified via item analysis.

3.2 Factor Analysis

Factor analysis was begun in the early 20th century attempts of Karl Pearson, Charles Spearman. The essential purpose of factor analysis is to describe, if possible, the covariance relationships among variables in terms of a few underlying, but unobservable, random quantities called factors. Factor analysis can be considered an extension of principal component analysis and attempts to approximatc the covariance matrix.

Factor analysis is a statistical technique used to find a set of unobserved, also known as latent, variables or factors that can account for the covariance among a larger set of observed, also known as manifest, variables. A factor is an unobservable variable that is assumed to influence observed variables. Factor analysis is also used to assess the validity, and reliability, of measurement scales. Through factor analysis, the underlying dimensions of the observed variables and the variables corresponding to each of the underlying dimensions can be identified. These underlying dimensions are the continuous latent variables or factors and the observed variables are the factor indicators. There are two types of factor analysis that are exploratory factor analysis (EFA) and confirmatory analysis.

Exploratory factor analysis (EFA) is a multivariate statistical method used to uncover the underlying structure of a relatively large set of variables. EFA is an exploratory technique to determine the dimensionality of a set of variables and observe the pattern of the factor loadings. It is commonly used when a priori hypothesis about factors or pattern of measurement variables. The theory behind factor analysis method is that the information gained about the interdependencies between observed variable can be used later to reduce the set of variables in dataset. Factor analysis is commonly used in biology, psychometrics, personality theories, marketing, product management, operations research and finance.

3.2.1 The Orthogonal Factor Model

The observable random vector **X**, with p components, has mean $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$. The factor model postulates that **X** is linearly dependent upon a few unobservable random variable random variables$F_1, F_2, \ldots, F_m$ called common factors, and p additional sources of variation$\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_p$, called errors or, sometimes, specific factors. In particular, the factor analysis model is

$$\begin{aligned} X_1 - \mu_1 &= \ell_{11}F_1 + \ell_{12}F_2 + \ell_{13}F_3 + \ldots + \ell_{1m}F_m + \varepsilon_1 \\ X_2 - \mu_2 &= \ell_{21}F_1 + \ell_{22}F_2 + \ell_{23}F_3 + \ldots + \ell_{2m}F_m + \varepsilon_2 \qquad (3.1) \\ &\vdots \\ X_p - \mu_p &= \ell_{p1}F_1 + \ell_{p2}F_2 + \ell_{p3}F_3 + \ldots + \ell_{pm}F_m + \varepsilon_p \end{aligned}$$

In matrix model,

$$\underset{(p\times 1)}{\mathbf{X}-\boldsymbol{\mu}} = \underset{(p\times m)}{\mathbf{L}}\ \underset{(m\times 1)}{\mathbf{F}} + \underset{(p\times 1)}{\boldsymbol{\varepsilon}} \qquad (3.2)$$

μ_i = mean of variable i

ε_i= ith specific factor

F_j = jth common factor

ℓ_{ij} = loading of the ith variable on the jth factor

The observable random vectors **F** and ε satisfy the following conditions:

F and ε are independent

$$\underset{(m\times 1)}{E(\mathbf{F}) = \mathbf{0}} \quad \text{and} \quad \underset{(m\times m)}{\text{Cov}(\mathbf{F}) = \mathbf{I}}$$

$$\underset{(p\times 1)}{E(\boldsymbol{\varepsilon}) = \mathbf{0},} \quad \text{and} \quad \underset{(p\times p)}{\text{Cov}(\boldsymbol{\varepsilon}) = \boldsymbol{\Psi}} \qquad (3.3)$$

where $\boldsymbol{\Psi}$ is a diagonal matrix.

Covariance Structure for the Orthogonal Factor Model

The orthogonal factor model implies a covariance structure for **X**.

$$\begin{aligned}\text{Cov}(\mathbf{X}) = \boldsymbol{\Sigma} &= E[(\mathbf{X}-\boldsymbol{\mu})(X-\boldsymbol{\mu})'] \\ &= \mathbf{L}\,E(\mathbf{FF}')\,\mathbf{L}' + \mathbf{L}\,E(\mathbf{F}\boldsymbol{\varepsilon}') + E(\boldsymbol{\varepsilon}\mathbf{F}')\,\mathbf{L}' + E(\boldsymbol{\varepsilon\varepsilon}') \\ &= \mathbf{LL}' + \boldsymbol{\Psi}\end{aligned}$$

$$\text{Cov}(\boldsymbol{\varepsilon}, \mathbf{F}) = E(\boldsymbol{\varepsilon}, \mathbf{F}') = 0$$

(OR) (3.4)

$$\text{Var}(X_i) = \ell_{i1} + \ell_{i2} + \ell_{i3} + \ldots + \ell_{im} + \psi_i$$

$$\text{Cov}(X_i, X_k) = \ell_{i1}\ell_{k1} + \ell_{i2}\ell_{k2} + \ell_{i3}\ell_{k3} + \ldots + \ell_{im}\ell_{km}$$

$$\text{Cov}(\mathbf{X}, \mathbf{F}) = E(\mathbf{X}-\boldsymbol{\mu})\mathbf{F}' = \mathbf{L}E(\mathbf{FF}') + E(\boldsymbol{\varepsilon}\mathbf{F}') = \mathbf{L}$$

(OR) (3.5)

$$\text{Cov}(X_i, F_j) = \ell_{ij}$$

The model $\mathbf{X} - \boldsymbol{\mu} = \mathbf{LF} + \boldsymbol{\varepsilon}$ is linear in the common factors. The portion of the variance of the ith variable contributed by the m common factor is called the ith communality. That portion of Var $(X_i) = \sigma_{ii}$ due to the specific factors is called the uniqueness, ot specific variance. Denoting the ith communality by h_i^2,

$$\sigma_{ii} = \ell_{i1}^2 + \ell_{i2}^2 + \ell_{i3}^2 + \dots + \ell_{im}^2 + \psi_i$$

Var (X_i) = communality + specific variance

or (3.6)

$$h_i^2 = \ell_{i1}^2 + \ell_{i2}^2 + \ell_{i3}^2 + \dots + \ell_{im}^2$$

and

$$\sigma_{ii} = h_i^2 + \psi_i$$

The ith communality is the sum of squares of the loadings of the ith variable on the m common factors.

3.3 Method of Estimation

The sample covariance matrix **S** is an estimator of the unknown population covariance matrix **Σ**. If the off-diagonal elements of **S** are small or those of the sample correlation matrix **R** essentially zero, the variables are not related, and a factor analysis will not prove useful. In these circumstances, the specific factors play the dominant role, whereas the major aim of factor analysis is to determine a few important common factors.

If **Σ** appears to deviate significantly from a diagonal matrix, then a factor model can be entertained and the initial problem is one of the estimating the factor loadings ℓ_{ij}^2 and specific variances ψ_i. The most popular methods of parameter estimation are the principal component method and maximum likelihood method. The solution from either method can be rotated in order to simplify the interpretation of factors. It is always prudent to try more than one method of solution; if the factor model is appropriate for the problem at hand, the solutions should be consistent with another.

The Principal Factor (and Principal Component Factor)

The spectral decomposition provides with one factoring of the covariance matrix Σ. Let Σ have eigenvalue-eigenvector pairs (λ_i, e_i) with $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \cdots \geq 0$.

Then

$$\Sigma=\lambda_1 e_1 e_1'+\lambda_2 e_2 e_2'+\lambda_3 e_3 e_3'+\ldots+\lambda_p e_p e_p' \quad (3.7)$$

$$\Sigma=\left[\sqrt{\lambda_1 e_1} \;\vert\; \sqrt{\lambda_2 e_2} \;\vert\; \sqrt{\lambda_3 e_3} \;\vert\; \cdots \;\vert\; \sqrt{\lambda_p e_p}\right]\begin{bmatrix} \sqrt{\lambda_1 e_1'} \\ --- \\ \sqrt{\lambda_2 e_2'} \\ --- \\ \sqrt{\lambda_3 e_3'} \\ --- \\ \vdots \\ --- \\ \sqrt{\lambda_p e_p'} \end{bmatrix}$$

The fits the prescribed covariance structure for the factor analysis model having as many factors as variable for the factor analysis model having as many factors as variables (m=p) and specific variances ψ_i=0 for all i. The loading matrix has jth column given by $\sqrt{\lambda_i e_i}$. This can be written

$$\underset{(p\times p)}{\Sigma} = \underset{(p\times p)}{\mathbf{L}} \; \underset{(p\times p)}{\mathbf{L}'} + \underset{(p\times p)}{\mathbf{0}} \quad (3.8)$$

A part from the scale factor $\sqrt{\lambda_i}$, the factor loadings on the jth factor ate the coefficients for the population jth principal component.

Although the factor analysis representation of Σ is exact, it is not particularly useful. It employs as many common factors as there are available and does not allow for any variation in the specific factors. These models explain the covariance structure in terms of just a few common factors. One approach, when the last p-m eigenvalues are small, is to neglect the contribution of $\lambda_m e_m e_{m+1}'+\ldots+\lambda_p e_p e_p'$ to Σ. Neglecting this contribution, the approximation is obtained

$$\Sigma=\left[\sqrt{\lambda_1}\mathbf{e}_1 \;\middle|\; \sqrt{\lambda_2}\mathbf{e}_2 \;\middle|\; \sqrt{\lambda_3}\mathbf{e}_3 \;\middle|\; \cdots \;\middle|\; \sqrt{\lambda_p}\mathbf{e}_p\right]\begin{bmatrix} \sqrt{\lambda_1}\mathbf{e}_1' \\ --- \\ \sqrt{\lambda_2}\mathbf{e}_2' \\ --- \\ \sqrt{\lambda_3}\mathbf{e}_3' \\ --- \\ \vdots \\ --- \\ \sqrt{\lambda_p}\mathbf{e}_p' \end{bmatrix}$$

$$\underset{(p\times p)}{\Sigma} = \underset{(p\times p)}{\mathbf{L}} \; \underset{(p\times p)}{\mathbf{L}'}$$

The approximate representation assumes that the specific factors ε are minor importance and can also be ignored in the factoring of Σ.

Allowing for specific factors, the approximation becomes

$$\Sigma = \mathbf{L}\mathbf{L}' + \Psi \qquad (3.10)$$

$$\Sigma=\left[\sqrt{\lambda_1}\mathbf{e}_1 \;\middle|\; \sqrt{\lambda_2}\mathbf{e}_2 \;\middle|\; \sqrt{\lambda_3}\mathbf{e}_3 \;\middle|\; \cdots \;\middle|\; \sqrt{\lambda_p}\mathbf{e}_p\right]\begin{bmatrix} \sqrt{\lambda_1}\mathbf{e}_1' \\ --- \\ \sqrt{\lambda_2}\mathbf{e}_2' \\ --- \\ \sqrt{\lambda_3}\mathbf{e}_3' \\ --- \\ \vdots \\ --- \\ \sqrt{\lambda_p}\mathbf{e}_p' \end{bmatrix}$$

$$+\begin{bmatrix} \psi_1 & 0 & 0 & \cdots & 0 \\ 0 & \psi_2 & 0 & \cdots & 0 \\ 0 & 0 & \psi_3 & \cdots & 0 \\ \vdots & \vdots & & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \psi_p \end{bmatrix} \qquad (3.11)$$

where $\psi_i = \sigma_{ii} - \sum_{j=1}^{m} \ell_{ij}^2$ for $i = 1, 2, 3, \ldots, p$

To apply this approach to a data set $\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \ldots, \mathbf{x}_n$, it is customary first to center the observations by subtracting the sample mean $\bar{\mathbf{x}}$. The centered observations

$$\mathbf{x}_j - \bar{\mathbf{x}} = \begin{bmatrix} x_{j1} \\ x_{j2} \\ x_{j3} \\ \vdots \\ x_{jp} \end{bmatrix} - \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \\ \bar{x}_3 \\ \vdots \\ \bar{x}_p \end{bmatrix} = \begin{bmatrix} x_{j1} - \bar{x}_1 \\ x_{j2} - \bar{x}_2 \\ x_{j3} - \bar{x}_3 \\ \vdots \\ x_{jp} - \bar{x}_p \end{bmatrix}, \quad n\ j=1, 2, 3,\ldots,n \qquad (3.12)$$

have the same sample covariance matrix, S, as the original observations.

In cases, where the units of the variables are not commensurate, it is usually describable to work with the standardized variables.

$$\mathbf{Z}_j = \begin{bmatrix} \frac{x_{1j} - \bar{x}_1}{\sqrt{s_{11}}} \\ \frac{x_{2j} - \bar{x}_2}{\sqrt{s_{22}}} \\ \frac{x_{3j} - \bar{x}_3}{\sqrt{s_{33}}} \\ \vdots \\ \frac{x_{pj} - \bar{x}_p}{\sqrt{s_{pp}}} \end{bmatrix}, \quad j=1, 2, 3,\ldots, n \qquad (3.13)$$

The sample covariance matrix is the sample correlation matrix, **R**, of the observations $\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \ldots, \mathbf{x}_n$.

The principal component factor analysis of the sample covariance matrix Sis specified in terms of its eigenvalue-eigenvector pairs $(\hat{\lambda}_1, \hat{e}_1)$, $(\hat{\lambda}_2, \hat{e}_2)$, $(\hat{\lambda}_3, \hat{e}_3)$,…,$(\hat{\lambda}_p, \hat{e}_p)$ where $\hat{\lambda}_1 \geq \hat{\lambda}_2 \geq \hat{\lambda}_3 \geq \ldots \geq \hat{\lambda}_p$.

Let m<p be the number of common factors. Then the matrix of estimated factor loadings ($\tilde{\ell}_{ij}$) is given by

$$\tilde{\mathbf{L}} = \left[\sqrt{\hat{\lambda}_1}\hat{e}_1 \;\middle|\; \sqrt{\hat{\lambda}_2,}\hat{e}_2 \;\middle|\; \sqrt{\hat{\lambda}_3,}\hat{e}_3 \;\middle|\; \cdots \;\middle|\; \sqrt{\hat{\lambda}_p,}\hat{e}_p \right] \qquad (3.14)$$

The estimate specific variances are provided by the diagonal elements of the matrix S -$\tilde{L}\tilde{L}'$, so

$$\tilde{\Psi} = \begin{bmatrix} \psi_1 & 0 & 0 & \cdots & 0 \\ 0 & \psi_2 & 0 & \cdots & 0 \\ 0 & 0 & \psi_3 & \cdots & 0 \\ \vdots & \vdots & & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \psi_p \end{bmatrix} \quad (3.15)$$

with $\psi_{ij} = s_{ii} - \sum_{i=1}^{m} \tilde{\ell}^2_{ij}$

Communalities are estimated as

$$\tilde{h}_i^2 = \tilde{\ell}_{i1}^2 + \tilde{\ell}_{i2}^2 + \tilde{\ell}_{i3}^2 + \ldots + \tilde{\ell}_{im}^2 \quad (3.16)$$

The principal component factor analysis of the sample correlation matrix is obtained by starting with **R** in place **S.**

Consider the residual matrix,

$$\mathbf{S} - (\tilde{\mathbf{L}}\tilde{\mathbf{L}} + \tilde{\Psi}) \quad (3.17)$$

resulting from the approximation of **S** by the principal component solution. The diagonal elements are zero. Analytically,

$$\text{Sum of squared entries of} (\mathbf{S} - (\tilde{\mathbf{L}}\tilde{\mathbf{L}} + \tilde{\Psi})) \leq \hat{\lambda}_{m+1} \leq \cdots \leq \hat{\lambda}_p \quad (3.18)$$

The contribution to the sample variance s_{ii} from the first common factor is $\tilde{\ell}_{i1}^2$. The contribution to the total sample variance $s_{11}, s_{22}, s_{33}, \ldots, s_{pp} = \text{tr}(S)$, from the first common factor is then

$$\tilde{\ell}_{11}^2 + \tilde{\ell}_{21}^2 + \tilde{\ell}_{31}^2 + \ldots + \tilde{\ell}_{p1}^2 = \left(\sqrt{\hat{\lambda}_1}\hat{e}_1\right)'\left(\sqrt{\hat{\lambda}_1}\hat{e}_1\right) = \hat{\lambda}_1$$

since the eigenvector $\hat{\mathbf{e}}_1$ has unit length.

In general,

$$\begin{pmatrix}\text{Proportion of the total} \\ \text{sample variance} \\ \text{due to jth factor}\end{pmatrix} = \begin{cases} \dfrac{\hat{\lambda}_j}{s_{11}+s_{22}+s_{33}+\cdots+s_{pp}} & \text{for a factor analysis of S} \\ \dfrac{\hat{\lambda}_j}{p} & \text{for a factor analysisofR} \end{cases} \quad (3.19)$$

Criterion is frequently used as a heuristic device for determining the appropriate number of common factors. The number of common factors retained in the model is increased until a suitable proportion of the total sample variance has been explained.

3.4 Factor Rotation

All factor loadings obtained from the initial loadings by an orthogonal transformation have the same ability to reproduce the covariance matrix. From matrix algebra, an orthogonal transformation corresponds to a rigid rotation of the coordinate axes. An orthogonal transformation of the factor loadings as well as the implied orthogonal transformation of the factors is called factor rotation.

If $\hat{\boldsymbol{L}}$ is the p×m matrix of estimated factor loadings obtained by any method then

If $\hat{\boldsymbol{L}}$ is the p × m matrix of estimated factor loadings obtained by any method then

$$\hat{\mathbf{L}}* = \hat{\mathbf{L}}\mathbf{T} \qquad \text{where} \qquad \mathbf{TT}' = \mathbf{T}'\mathbf{T} = \mathbf{I} \qquad (3.20)$$

is a p × m matrix of rotated loadings.

The estimated covariance matrix remains unchanged, since

$$\mathbf{L}\hat{\mathbf{L}} + \boldsymbol{\Psi} = \hat{\mathbf{L}}\mathbf{T}'\mathbf{T}\hat{\mathbf{L}} + \boldsymbol{\Psi} = \hat{\mathbf{L}}^{*}\hat{\mathbf{L}}^{*\prime} + \boldsymbol{\Psi} \qquad (3.21)$$

Indicates that the residual matrix, $\mathbf{S}_n - \mathbf{L}\hat{\mathbf{L}} - \boldsymbol{\Psi} = \mathbf{S}_n - \hat{\mathbf{L}}^{*}\hat{\mathbf{L}}^{*\prime} - \boldsymbol{\Psi}$ remains unchanged. Moreover, the specific variances ψ_i and the communalities h_i^2 are unaltered. Thus, it is immaterial whether **L** or $\hat{\mathbf{L}}^{*}$ is obtained.

Since the original loadings may not be readily interpretable, it is usual practice to rotate them until a simpler structure is achieved. Each variable loads highly on a single factor and has small to moderate loadings on the remaining factors. It is possiblc to get this simple structure and the rotated loadings for the decathlon data provide a clearly pattern.

Rotation method is factor structure more interpretable. Rotation may be orthogonal when factors are uncorrelated with one another or oblique when factors are correlated with one another. The choice of rotation is both empirically and theoretically driven.

3.4.1 Varimax Rotation Method

Orthogonal rotation shifts the factors in the factor space maintaining 90 degrees angle of the factors to one another to achieve the best simple structure. This rotation strategy maintains the perfectly uncorrelated nature of the factors after the solution is rotated and often aids in the interpretation process since uncorrelated factors are easier to interpret. In theory, the results of an orthogonal rotation are likely to be replicated in future studies since there is less sampling error in the orthogonal rotation due to less capitalization on chance that would occur if more parameters were estimated, as is the case in oblique rotation.

Varimax rotation method is one of the most popular orthogonal rotation techniques is rotation to the varimax criterion developed by Kaiser. In statistics, a varimax rotation method is used to simplify the expression of a particular sub-space in terms of just a few major items. If the actual coordinate system is unchanged, it is the orthogonal basis that is being rotated to align with those coordinates. In this technique, the factors are that every observed variable has a large factor pattern/structure coefficient on only one of the factors. Other orthogonal rotation methods are quartimax and equimax.

3.4.2 Oblique Rotation Method

Oblique rotation method allows for correlated factors instead of maintaining independence between the rotated factors. The oblique rotation process does not require that the reference axes be maintained at 90 degrees angle. This rotation strategy is termed oblique because the angles between the factors becomes greater or less than the 90 degrees angle. Oblique rotation method is more flexible because the axes need not be orthogonal. The two major method of oblique rotation method are direct oblimin and promax. Oblimin rotation is that factors are allowed to be correlated and diminished interpretability. Promx rotation method is computationally faster than oblimin rotation and used for the large datasets.

3.5 Factor Scores by Regression Model

In factor analysis, interest is usually centered on the parameters in the factor model. The estimated values of the common factors, called factor score may also be required. These quantities are often used for diagnostic purpose, as well as inputs to a subsequent analysis.

Factor scores are not estimate of unknown parameters in the usual sense. Rather they are estimates of vales for the unobserved random vectors $\mathbf{F}_j$, j = 1, 2, 3,…,n. That is, factor scores

$$\mathbf{F}_j = \text{estimated of the values} f_j \text{ attained by } \mathbf{F}_j \text{ for } j = 1, 2, 3, \ldots, n$$

The estimation situation is complicated by the factor that the unobserved quantities$\mathbf{f}_j$ and $\boldsymbol{\varepsilon}_j$ outnumber the observation$\mathbf{x}_j$.

Starting again with the original factor model$\mathbf{X} - \boldsymbol{\mu} = \mathbf{L}\,\mathbf{F} + \boldsymbol{\varepsilon}$, one initially treats the loadings matrix **L** and specific variance matrix as known. The common factors **F** and the specific factors (or error)$\boldsymbol{\varepsilon}$ are jointly normally distributed with means and covariances. Therefore, the linear combination$\mathbf{X} - \boldsymbol{\mu} = \mathbf{L}\,\mathbf{F} + \boldsymbol{\varepsilon}$has an $\mathbf{N}_p(0, \mathbf{LL'}+\boldsymbol{\Psi})$ distribution. Moreover, the joint distribution of $(\mathbf{X} - \boldsymbol{\mu})$and **F** is $\mathbf{N}_{m+p}(0,\boldsymbol{\Sigma}^*)$, where

$$\boldsymbol{\Sigma}^* = \begin{bmatrix} \boldsymbol{\Sigma} = \mathbf{LL'} + \boldsymbol{\Psi} & \mathbf{L} \\ \mathbf{L'} & \mathbf{I} \end{bmatrix} \quad (3.22)$$

and **0** is an (m + p) × 1 vector of zeros. The conditional distribution of F|x is multivariate normal with

$$\text{mean} = E(\mathrm{F}|\mathrm{x}) = \mathbf{L'}\boldsymbol{\Sigma}^{-1}(\mathrm{x} - \boldsymbol{\mu}) = \mathbf{L'}(\mathbf{LL'} + \boldsymbol{\Psi})^{-1}(\mathrm{x} - \boldsymbol{\mu}) \quad (3.23)$$

and

$$\text{covariance} = \mathrm{Cov}(\mathrm{F}|\mathrm{x}) = \mathbf{I} - \mathbf{L'}\boldsymbol{\Sigma}^{-1}\mathbf{L} = \mathbf{I} - \mathbf{L'}(\mathbf{LL'} + \boldsymbol{\Psi})^{-1}\mathbf{L} \quad (3.24)$$

The quantities$\mathbf{L'}(\mathbf{LL'} + \boldsymbol{\Psi})^{-1}$ are the coefficient in a multivariate regression of the factors on the variables. Estimates of these coefficients produce factor scores that are analogous to the estimates the conditional mean values in multivariate regression analysis. Consequently, given any vector of observations $\mathbf{x}_j$ and taking the maximum likelihood estimates $\hat{\mathbf{L}}$ and $\boldsymbol{\Psi}$ as the true values, the jth factor score vector is given by

$$\hat{\mathbf{f}}_j = \hat{\mathbf{L}}\hat{\boldsymbol{\Sigma}}^{-1}(\mathbf{x}_j - \bar{\mathbf{x}}) = \hat{\mathbf{L}}'(\hat{\mathbf{L}}\hat{\mathbf{L}}' + \hat{\boldsymbol{\Psi}})^{-1}(\mathbf{x}_j - \bar{\mathbf{x}}) \qquad j = 1, 2, 3, \ldots, n \qquad (3.25)$$

The calculation of $\hat{\mathbf{f}}_j$ can be simplified by using the matrix identity

$$\hat{\mathbf{L}}'(\hat{\mathbf{L}}\hat{\mathbf{L}}' + \hat{\boldsymbol{\Psi}})^{-1} = (\mathbf{I} + \hat{\mathbf{L}}'\hat{\boldsymbol{\Psi}}^{-1}\hat{\mathbf{L}})^{-1}\hat{\mathbf{L}}'\hat{\boldsymbol{\Psi}}^{-1} \qquad (3.26)$$

Therefore $\hat{\mathbf{F}}_j = (\mathbf{I} + \hat{\mathbf{L}}'\hat{\boldsymbol{\Psi}}^{-1}\hat{\mathbf{L}})^{-1}\hat{\mathbf{L}}'\hat{\boldsymbol{\Psi}}^{-1}(\mathbf{x}_j - \bar{\mathbf{x}}), \quad j = 1, 2, 3, \ldots, n$

If a correlation matrix is factored,

$$\hat{\mathbf{F}}_j = \hat{\mathbf{L}}'_2\,\hat{\boldsymbol{\rho}}^{-1}\mathbf{Z}_j, \; j = 1, 2, 3, \ldots, \qquad (3.27)$$

$$\mathbf{Z}_j = \mathbf{D}^{-1/2}(\mathbf{x}_j - \bar{\mathbf{x}}) = \begin{bmatrix} \frac{x_{1j} - \bar{x}_1}{\sqrt{s_{11}}} \\ \frac{x_{2j} - \bar{x}_2}{\sqrt{s_{22}}} \\ \frac{x_{3j} - \bar{x}_3}{\sqrt{s_{33}}} \\ \vdots \\ \frac{x_{pj} - \bar{x}_p}{\sqrt{s_{pp}}} \end{bmatrix} \qquad \text{and}$$

$$\hat{\boldsymbol{\rho}} = \hat{\mathbf{L}}_2\hat{\mathbf{L}}'_2 + \boldsymbol{\Psi}_2$$

If rotated loadings $\hat{\mathbf{L}}* = \hat{\mathbf{L}}\mathbf{T}$ are used in place of the original loadings, the subsequent factor scores $\hat{\mathbf{F}}_j^*$ are related $\hat{\mathbf{F}}_j$ by

$$\hat{\mathbf{F}}_j^* = \mathbf{T}'\hat{\mathbf{F}}_j, \; j = 1, 2, 3, \ldots, n$$

A numerical measure of agreement between the factor scores generated from two different calculation methods is provided by the sample correlation coefficient between scores on the same factor.

3.5.1 Testing of Adequacy of the Approach

In factor analysis, Kaiser-Meyer-Olkin and Bartlett's Test of Sphericity is an important role for accepting the sample adequacy. Kaiser-Meyer-Olkin and Bartlett's test of Sphericity is a measure of sampling adequacy that is recommended to check the case to variable ratio for the analysis being conducted. Henry Kasier (1970) introduced a Measure of Sampling Adequacy (MSA) of factor analytic data matrices. Kasier and Rice (1974) then modified it.

Kaiser-Meyer-Olkin (KMO) test is a measure of how suited the data is for factor analysis. The statistic is a measure of the proportion of variance among variables that might be common variance. The lowest the proportion, the more suited the data is to factor analysis. While the values of KMO ranges between 0 and 1, the world over accept index is over 0.6. Kaiser-Meyer-Olkin (KMO) values between 0.8 and 1 indicate that the sampling is adequate. If this value is less than 0.6 indicate, the sampling is not adequate and remedial action should be taken. Kaiser-Meyer-Olkin (KMO) values close to zero means that the large partial correlations compared to the sum of correlations. In other words, there are widespread correlations which are large problem for factor analysis.

Also, Bartlett's Test of Sphericity relates to the significance of the study and thereby shows the validity and suitability of the responses collected to the problem being addressed through the study. Bartlett's Test of Sphericity compares the correlation matrix (a matrix of Pearson correlations) to the identity matrix. In other word, it checks if there is a redundancy between variables. For factor analysis, the Bartlett's Test of Sphericity must be less than 0.05. For a large sample, Bartlett's Test of Sphericity approximates a chi-square distribution. However, Bartlett's Test of Sphericity compares the observed correlation matrix to the identify matrix.

3.6 Confirmatory Factor Analysis

Confirmatory factor analysis (CFA)is a multivariate technique that uses structural equation model. Confirmatory factor analysis is used to study the relationships between a set of observed variables and a set of continuous latent variables. When the observed variables are categorical, CFA is also referred to as item response theory (IRT) analysis (Fox, 2010; Linder, 2016). CFA with covariates includes models where the relationship between factors and a set of covariates are studies to understand measurement invariance and population heterogeneity. These models can include direct effects, that is, the regression of a factor indicator on a covariate in order to study measurement non-invariance. CFA can include correlated residuals when minor factors influence the variables. Although CFA is most directly relevant for evaluating the internal structure of a scale, it also provides information related to the internal consistency of the scale.

Additionally, CFA can be used to evaluate convergent and discriminant evidence. It is common to display confirmatory factor models as path diagrams in which squares represent observed variables and circles represent the latent concepts. In diagram of CFA, single-head arrows are used to imply a direction of assumed causal influence and double-head arrows are used to represent covariance between the latent variables or factors.

A fundamental equation of the common factor model is

$$y_j = \lambda_{j1}\eta_1 + \lambda_{j2}\eta_2 + \lambda_{j3}\eta_3 + \ldots + \lambda_{jm}\eta_m + \varepsilon_j \qquad (3.28)$$

where

y_j = the j^{th} of p indicators (j = 1, 2, 3, ... , p)

λ_{jm}= the factor loading relating variable j to the m^{th} factor η

ε_j = the variance that is unique to indicator y_j

The model matrix terms,

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_p \end{bmatrix} = \begin{bmatrix} \lambda_{11} & \lambda_{12} & \lambda_{13} & \cdots & \lambda_{1m} \\ \lambda_{21} & \lambda_{22} & \lambda_{23} & \cdots & \lambda_{2m} \\ \lambda_{31} & \lambda_{32} & \lambda_{33} & \cdots & \lambda_{3m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \lambda_{p1} & \lambda_{p2} & \lambda_{p3} & \cdots & \lambda_{pm} \end{bmatrix} \begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \vdots \\ \eta_m \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \vdots \\ \varepsilon_p \end{bmatrix} \qquad (3.29)$$

$$\underset{(p \times 1)}{\mathbf{Y}} = \underset{(p \times m)}{\mathbf{\Lambda}} \ \underset{(m \times 1)}{\boldsymbol{\eta}} + \underset{(p \times 1)}{\boldsymbol{\varepsilon}}$$

Assume that,

$$E(\boldsymbol{\eta}) = \underset{(m \times 1)}{\mathbf{0}}, \qquad V(\boldsymbol{\eta}) = \underset{(m \times m)}{\mathbf{\Psi}}$$

$$\underset{(p \times 1)}{E(\boldsymbol{\varepsilon}) = \mathbf{0}}, \qquad \underset{(p \times p)}{V(\boldsymbol{\varepsilon}) = \boldsymbol{\Theta}}$$

$$\underset{(p \times p)}{E(\boldsymbol{\eta\eta}') = \boldsymbol{\Psi}}, \qquad \underset{(p \times p)}{E(\boldsymbol{\varepsilon\varepsilon}') = \boldsymbol{\Theta}} \quad \text{and} \quad \underset{(p \times m)}{\mathrm{Cov}(\boldsymbol{\varepsilon}, \boldsymbol{\eta}) = \mathbf{0}}$$

The variance of **y** is

$$V(\mathbf{y}) = \boldsymbol{\Sigma} = E(\mathbf{yy}')$$

$$= E\,[(\boldsymbol{\Lambda}\boldsymbol{\eta} + \boldsymbol{\varepsilon})(\boldsymbol{\Lambda}\boldsymbol{\eta} + \boldsymbol{\varepsilon})']$$

$$= \boldsymbol{\Lambda}\, E(\boldsymbol{\eta\eta}')\, \boldsymbol{\Lambda}' + \boldsymbol{\Lambda}\, E(\boldsymbol{\eta\varepsilon}') + E(\boldsymbol{\varepsilon\eta}')\, \boldsymbol{\Lambda}' + E(\boldsymbol{\varepsilon\varepsilon}')$$

so that

$$\boldsymbol{\Sigma} = \boldsymbol{\Lambda\Psi\Lambda}' + \boldsymbol{\Theta} \qquad (3.30)$$

$$\boldsymbol{\Psi} = \begin{bmatrix} \psi_{11} & 0 & 0 & \cdots & 0 \\ 0 & \psi_{22} & 0 & \cdots & 0 \\ 0 & 0 & \psi_{33} & \cdots & 0 \\ & \vdots & & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \psi_{pm} \end{bmatrix}$$

$$\boldsymbol{\Theta} = \begin{bmatrix} \theta_1 & 0 & 0 & \cdots & 0 \\ 0 & \theta_2 & 0 & \cdots & 0 \\ 0 & 0 & \theta_3 & \cdots & 0 \\ & \vdots & & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \theta_p \end{bmatrix}$$

where $\boldsymbol{\Sigma}$ = the p × p symmetric covariance matrix of p indicators

$\boldsymbol{\Lambda}$ = the p × m matrix of factor loadings λ

$\boldsymbol{\Psi}$ = the m × m symmetric correlation matrix of the factor correlations (1 × 1)

$\boldsymbol{\Theta}$ = the p × p diagonal matrix of unique variances ε.

3.6.1 Estimation of Confirmatory Factor Analysis Model

The objective of CFA is to obtain estimates for each parameter of the measurement model (i.e., factor loadings, factor variances and covariances, indicator error variances and possibly error covariances) that produce a predicted variance–covariance matrix (symbolized as Σ) that resembles the sample variance–covariance matrix (symbolized as S) as closely as possible. For instance, in overidentified models, perfect fit is rarely achieved (i.e., $\Sigma \neq S$). Thus, in the case of a CFA model, the goal of the analysis is to find a set of factor loadings that yield a predicted covariance matrix (Σ) that best reproduces the input matrix (S). This process entails a fitting function, a mathematical operation to minimize the difference between Σ and S. By, the fitting function most widely used in applied CFA research (and SEM, in general) is maximum likelihood (ML). The fitting function that is minimized in maximum likelihood (ML) is:

$$FML = \ln |S| - \ln |\Sigma| + \text{trace}\,[(S)(\Sigma\text{-}1)] - p \qquad (3.31)$$

where $|S|$ is the determinant of the input variance–covariance matrix, $|\Sigma|$ is the determinant of the predicted variance–covariance matrix, p is the order of the input matrix (i.e., the number of input indicators), and ln is the natural logarithm. The determinant and trace summarize important information about matrices such as S and Σ.

The determinant is a single number (i.e., a scalar) that reflects a generalized measure of variance for the entire set of variables contained in the matrix. The trace of a matrix is the sum of values on the diagonal (e.g., in a variance–covariance matrix, the trace is the sum of variances). The objective of ML is to minimize the differences between these matrix summaries (i.e., the determinant and trace) for S and Σ.

The underlying principle of ML estimation in CFA is to find the model parameter estimates that maximize the probability of observing the available data if the data were collected from the same population again. In other words, ML aims to find the parameter values that make the observed data most likely (or conversely, maximize the likelihood of the parameters given the data). One reason why ML is widely used in CFA model estimation is that it possesses desirable statistical properties, such as the ability to provide standard errors (SEs) for each of the model's parameter estimates. These SEs are used for conducting statistical significance tests of the parameter estimates (i.e., z = unstandardized parameter estimate divided by its SE) and for determining the precision of these estimates. Moreover, FML is used in the calculation of many goodness-of-fit indices.

3.6.2 Descriptive Goodness of Fit Indices

The classic goodness-of-fit index is chi-square χ^2. Under typical ML model estimation, χ^2 is calculated as:

$$\chi^2 = FML\,(N - 1) \qquad (3.32)$$

where χ^2 is calculated by multiplying FML by N instead of N – 1.

The model $\chi2$ exceeds the critical value, and thus the null hypothesis that $S = \Sigma$ is rejected. Thus, a statistically significant $\chi2$ (latent variable software provide the exact probability value of the model $\chi2$) supports the alternate hypothesis that $S \neq \Sigma$, meaning that the model estimates do not sufficiently reproduce the sample variances and covariances. Fit indices can be broadly characterized as falling under three categories: absolute fit, fit adjusting for model parsimony, and comparative or incremental fit. The normed chi-square that is the statistic of chi-square divided by degree freedom and that should be less than 5.

3.6.3 Absolute Fit

Absolute fit indices assess model fit at an absolute level; in various ways, they evaluate the reasonability of the hypothesis that $S = \Sigma$ without taking into account other aspects such as fit in relation to more restricted solutions. Thus, χ^2 is an example of an absolute fit index. Another index that falls in this category is the standardized root mean square residual (SRMR). Conceptually, the SRMR can be viewed as the average discrepancy between the correlations observed in the input matrix and the correlations predicted by the model.

A similarly named index, the root mean square residual (RMR), reflects the average discrepancy between observed and predicted covariances. However, the RMR can be difficult to interpret because its value is affected by the metric of the input variables; thus, the SRMR is generally preferred. The SRMR can be calculated by summing the squared elements of the residual correlation matrix and dividing this sum by the number of elements in this matrix (on and below the diagonal), that is,

$$b = \frac{p\,(p+1)}{2} \tag{3.33}$$

where b is the number of elements of the input matrix, and p is the number of indicators included in the input matrix and taking the square root (SQRT) of this result. The SRMR can take a range of values between 0.0 and 1.0, with 0.0 indicating a perfect fit (i.e., the smaller the SRMR, the better the model fit).

3.6.4 Parsimony Correction

Although sometimes grouped under the category of absolute fit, these indices differ from χ^2, SRMR, and so forth, by incorporating a penalty function for poor

model parsimony. A widely used and recommended index from this category is the root mean square error of approximation (RMSEA; Steiger & Lind, 1980). The RMSEA is a population-based index that relies on the noncentral 2 distribution, which is the distribution of the fitting function when the fit of the model is not perfect. The noncentral χ^2 distribution includes a noncentrality parameter (NCP), which expresses the degree of model misspecification. The NCP is estimated as $\chi^2 - df$ (if the result is a negative number, NCP = 0). When the fit of a model is perfect, NCP = 0 and a central χ^2 distribution holds. When the fit of the model is not perfect, the NCP is greater than 0 and shifts the expected value of the distribution to the right of that of the corresponding central χ^2. The RMSEA is an "error of approximation" index because it assesses the extent to which a model fits reasonably well in the population (as opposed to testing whether the model holds exactly in the population; cf. χ^2).
To foster the conceptual basis of the calculation of RMSEA, the NCP is rescaled to the quantity $d := \chi^2 - \frac{df}{(N-1)}$. The RMSEA is then computed:

$$\text{RMSEA} = \text{SQRT}\left[\frac{d}{df}\right] \tag{3.34}$$

where df is the model degree freedom. The noncentral χ^2 distribution can be used to obtain confidence intervals for RMSEA (a 90% interval is typically used). The confidence interval indicates the precision of the RMSEA point estimate. Specifically, "close" fit (CFit) is operationalized as RMSEA values less than or equal to .08.

3.6.5 Comparative Fit

Comparative fit indices (also referred to as incremental fit indices) evaluate the fit of a user-specified solution in relation to a more restricted, nested baseline model. Typically, this baseline model is a "null" or "independence" model in which the covariances among all input indicators are fixed to zero, although no such constraints are placed on the indicator variances. The comparative fit index (CFI; Bentler, 1990) is computed as follows:

$$\text{CFI} = \frac{1 - \max\left[(\chi^2_T - df_T), 0\right]}{\max\left[(\chi^2_T - df_T), (\chi^2_B - df_B), 0\right.} \tag{3.35}$$

where χ^2_T is the χ^2 value of the target model (i.e., the model under evaluation), df_T is the df of the target model, χ^2_B is the χ^2 value of the baseline model (i.e., the "null" model), and df_B is the df of the baseline model; max indicates to use the largest value.

The CFI has a range of possible values of 0.0 to 1.0, with values closer to 1.0 implying good model fit. Like the RMSEA, the CFI is based on the noncentrality parameter, meaning that it uses information from expected values of $\chi^2{}_T$ or $\chi^2{}_B$ under the noncentral χ^2 distribution associated with $S \neq \Sigma$.

3.7 Comparing Two Means

The compare means t-test or independent sample test is used to compare the mean of a variable in one group to the mean of same variable in one, or more, other groups. In general, the population standard deviations (σ_1 and σ_2) are not known, and they are estimated by the sample standard deviations (s_1 and s_2). The test statistic is defined by the two- sample t statistic:

$$t = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_1^2}{n_2}}}$$

where $\bar{x}_1$ is the first sample mean and $\bar{x}_2$ is the second sample mean. μ_1 is the first population mean and μ_2 is the second population mean. s_1 is the standard deviations of first population and s_2 is the standard deviations of second population. n_1 and n_2 are the sample sizes of first and.

Although the two-sample t statistics does not have an exact t distribution. The t(k) distribution with an approximation for the degrees of freedom k is used to find approximate values of t^* for confidence intervals and to find approximate p-values for significance tests. The distribution is be approximated by a t distribution with degrees of freedom given by

$$df = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\frac{1}{n_1 - 1}\left(\frac{s_1^2}{n_1}\right)^2 + \frac{1}{n_2 - 1}\left(\frac{s_2^2}{n_2}\right)^2}$$

It was discovered by Satterthwaite in 1946 and the Satterthwaite approximation is quite accurate when both sample sizes n_1 and n_2 are 5 or large.

CHAPTER IV

ANALYSIS OF SOCIAL MEDIA IMPACT ON BAGO UNIVERSITY STUDENTS

This chapter presents the analysis of the social media usage of students and impact on students in BAGO University based on the results of data collected from 550 students. The statistical analyses used in this study include reliability test, factor analysis, confirmatory factor analysis and independent sample test. The data for this study is collected from personal interviews based on a survey questionnaire. The students' demographic characteristics and the most uses of social media were firstly gathered and the usages and impacts of social media were explored. The questionnaire included a total of 40 items using a 5-point Likert-Scale ranging from strongly disagree (1) to strongly agree (5).

4.1 Survey design

To obtain the required information on social media utilization and the effects of social media survey was conducted in BAGO University. The study population was approximately 9031 students of the reproductive age (16-24). The data collection method used in this survey was personal interview method.

4.1.1 Determining of the Sample Design

The analytical cross section study was used to collect information that aimed at addressing the objective of the study. The sampling design that has been employed for data collection was a stratified random sampling. This sampling method is very useful for complete sampling frame. In line with this sampling method is five education levels in this university were taken to be the stratum. The education levels were stratified into stratum I (First year), stratum II (Second year), stratum III (Third year), stratum IV (Fourth year) and stratum V (Master). Then, the students were selected with simple random sampling method (without replacement) from each stratum. The required data were collected from selected by using the questionnaires and though face-to-face interview method.

4.1.2 Determining the Sample Size

In this study, the proportion of student who used social media is assumed to be 0.5. The appropriate stratified random sample is chosen with a bound on the error of estimation B of 0.05(assumed) by using the following formula:

$$n \geq \frac{\Sigma(N_h^2 \hat{p}_h \hat{q}_h / w_h)}{N^2 D + \Sigma_{h=1}^{L} N_h \hat{p}_h \hat{q}_h}$$

where

N_h= Number of units in stratum h (each education level)

$\hat{p}_h$= proportion of students who have used social media for stratum h (maximum possible proportion = 0.5)

$\hat{q}_h$ = 1- $\hat{p}_h$= proportion of students who have not used social media for stratum h (each education level)

B = Bound on the error of estimation= 0.5

$$D = \frac{B^2}{4} = \frac{(0.05)^2}{4} = 0.000625$$

$w_h = \frac{N_h \hat{p}_h \hat{q}_h}{\sum N_h \hat{p}_h \hat{q}_h}$ = the fraction of observations allocated to stratum h (education level)

Table (4.1) Sample Sizes from Each Strata

Strata	N_h	$\hat{p}_h$	$\hat{q}_h$	$N_h\hat{p}_h\hat{q}_h$	$w_h = \frac{N_h\hat{p}_h\hat{q}_h}{\sum N_h\hat{p}_h\hat{q}_h}$	$N_h^2\hat{p}_h\hat{q}_h/w_h$	Sample Sizes of Each Strata $n_h = nw_h$
I	3369	0.5	0.5	842	0.3730	7607346.515	n_1= 550 x 0.3730 = 205
II	2447	0.5	0.5	612	0.2709	5525848.099	n_2 = 550 x 0.2709 = 149
III	1824	0.5	0.5	456	0.2019	4119583.952	n_3 = 550 x 0.2019 = 111
IV	1210	0.5	0.5	303	0.1340	2731529.851	n_4 = 550x 0.1340 = 74
V	181	0.5	0.5	45	0.0200	409512.5	n_5= 550 x 0.0200 = 11
	9031			2258			n = 550

The sample size is

$$n \geq \frac{20393820.92}{(9031)^2 \times 0.000625 + 2258}$$

$$\geq 383.1121 \approx 384$$

The required sample size is at least 384 students. However, in many social research surveys, the response rates are typically well below 100%. Therefore, the required sample size (70% response rate assumed) is 550 (384/0.70) students. Since the cost of sampling within each education level (stratum) does not vary from stratum to stratum, the sample size of each stratum is determined by using the following Neyman allocation.

$$n_h = n \times w_h$$

where

n_h = sample size for stratum h.

The corresponding allocation for each stratum (educational level) is presented in Table (4.1). The sample sizes for each stratum are 205, 149, 111, 74 and 11 respectively.

4.2 The Reliability Analysis of the Factors

Firstly, the items of social media usages and the effects of social media impact on students were conducted with reliability analysis. The reliability and the internal consistency of the items analyses were performed on the survey data. The reliability of the items according to the factors and general was.calculated by using Cronbach's alpha. Reliability analysis value for the overall items and each factor are presented in Table (4.2).

The Cronbach's alpha coefficient for eight factors ranged from 0.621 to 0.787 for the eight factors such as are learning utilization, usable place, destructive effect, addiction, multiple uses, gratification, health problem and personal uses. The results of each factor are reliable because alpha coefficient of each factor is more than 0.5 which is acceptable value. By examine the item-total statistics, the Cronbach's alpha reliability coefficient is calculated as 0.876 which indicates a high level of internal consistency for the overall items with this specific sample. In the reliability analysis, the Cronbach's alpha coefficient for learning utilization was 0.787 and that for usable place, destructive effect and addiction are 0.746, 0.713 and 0.714 respectively. The Cronbach's alpha coefficient for multiple uses, gratification and health problem are 0.654, 0.682 and 0.699 respectively. The last factor, personal uses is 0.621 which is more than the minimum value for accepting value.

Table (4.2)
Reliability Analysis Results

No.	Factor	Cronbach's Alpha	Number of items
1	Learning Utilization	0.787	7
2	Usable Place	0.746	6
3	Destructive Effect	0.713	5
4	Addiction	0.714	4
5	Multiple Uses	0.654	5
6	Gratification	0.682	5
7	Health Problem	0.699	4
8	Personal Uses	0.621	3
Total	All items	0.876	39

Source: Survey data

4.3 Factor analysis

Factor analysis was used 40 likert-items to construct the factors that related to social media usage of the survey done among university students. The 40 items are learning international language, discussion lesson, asking lesson, searching education information, reading online-book, sharing education knowledge and reading ism, admonishment and liters, online teaching, library, park, canteen, bus stop, leisure placement and wifi free place, neglect household chores, incomplete in lessons, facilitates laziness, waste time and conflict within family, disfavor for hanging out with friends, disfavor for spending time with friends, dislike for watching TV and rejection for doing sports, usage for philanthropy, watching movies, drama series and funny videos, listening international songs, playing games and the conversation with family and friends, easy connection, developed in opinions, advancement of knowledge and development in personal relationships, limitation on gymnastics, physical problem, loss of appetite and deprivation, usage for beauty and fashion, buying and selling in online shopping.

The principal factor method was used to generate the initial solution. The total variance explained at eight factors (learning utilization, usable place, destructive effect, addiction, multiple uses, gratification, health problem and personal uses) are 50.47% of the overall variance and their eigenvalues are greater than 1. Items of each factor are greater than 0.4. From the varimax-rotated factor matrix, eight factors with 39 variables are defined by the original 40 variables. One items (online-teaching) was subtracted from the measurement since online-teaching was not determinative of which factors is measured.

The Bartlett Test of Sphericity and Kaiser-Meyer-Olkin (KMO) are performed through the data set to evaluate whether factor analysis is suitable or not for this study. The Bartlett Test of Sphericity is significant at 0.001 level ($p<0.001$) and the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy is 0.86 which is merietorious. The Kaiser-Meyer-Olkin (KMO) ranges from 0 to 1 where greater value indicates high level of suitability and a value greater than 0.7 is statistically acceptable. Therefore, factor analysis is considered as an appropriate technique for analyzing factor loading. The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett Test of Sphericity are given in Table (4.3a).

Table (4.3a)

Kaiser-Meyer-Olkin (KMO) and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	.861
Bartlett's Test of Sphericity (Approx. Chi-Square) Degree of freedom(df) p-value	5956.019 780 0.000

The scree plot gives the number of factors of fast drops or fracture points as seen in the Figure (4.1). According to scree plot (eigenvalue graph), the number of factors in the items can be limited to eight. After the eighth point are small and the distances between then are very close and similar in the eigenvalue graph.

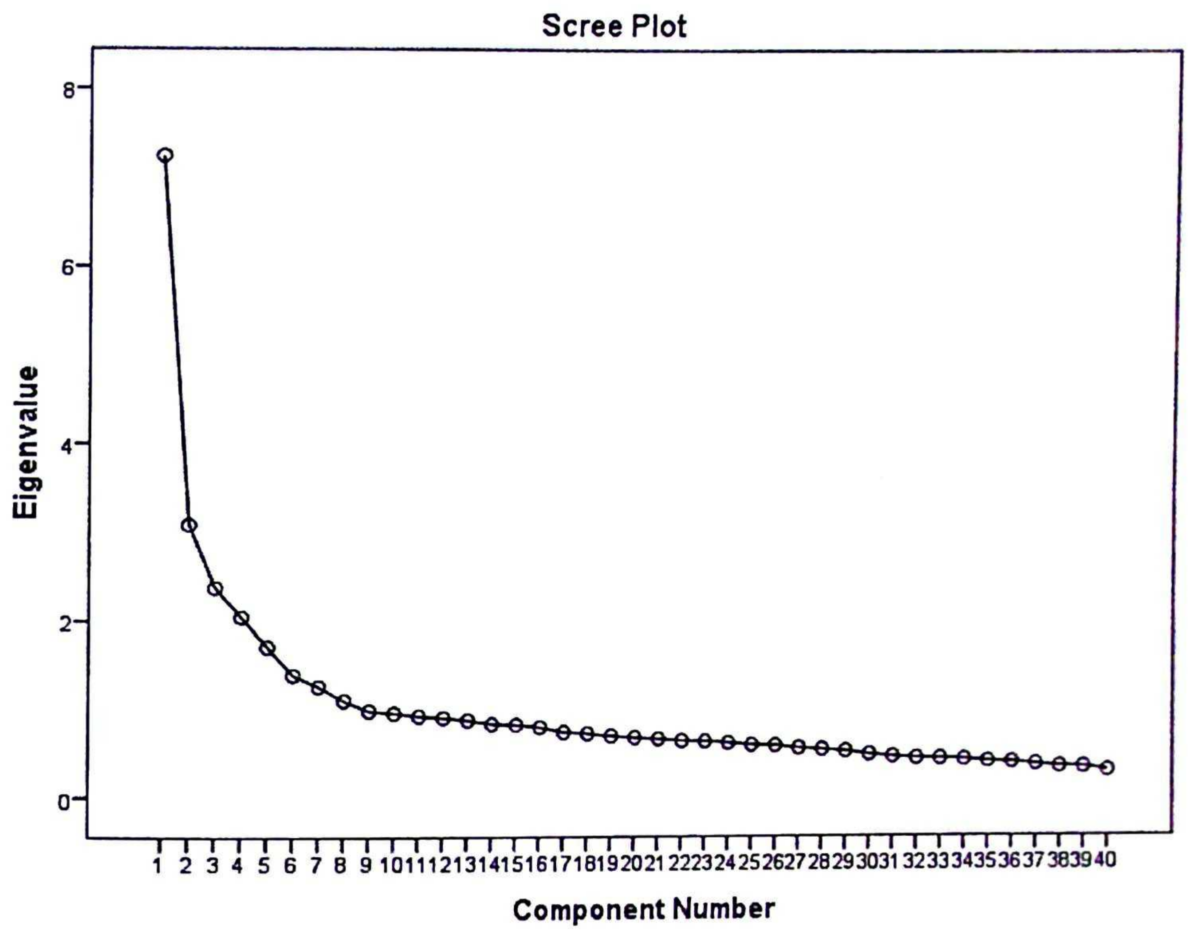

Figure (4.1). The Scree Plot for the Initial Variables

The results of factor analysis are illustrated in Table (4.3b). The initial stage represents the eigenvalue of each factor, the percentage of variance explained and the cumulative percentage. According to eigenvalue, the eight factors are extracted because their eigenvalue are greater than 1. If the eight factors (learning utilization, usable place, sad impact, addiction, multiple uses, gratification, health problem and personal uses) are extracted, then 50.468% of the variance would be explained.

Factor 1 is learning utilization and comprise of seven items. Factor 1explains 18.098% of the variance in the data with an eigenvalue of 7.239. This factor consists learning international language (LU1), discussion lesson (LU2), asking lesson (LU3), searching education information (LU4), reading online-book (LU5), sharing education knowledge (LU6) and reading ism, admonishment and liters (LU7) with factor loading ranging from 0.458 to 0.721.

Factor 2 is usable place and comprise of six items. Factor 2 explains 7.706% of the variance in the data with an eigenvalue of 3.083. The items of this factor are library (UP1), park (UP2), canteen (UP3), bus stop (UP4), leisure placement (UP5) and wifi free place (UP6) with factor loading ranging from 0.453 to 0.753.

Factor 3 is destructive effect and comprise of five items. Factor 3explains 5.929% of the variance in the data with an eigenvalue of 2.372. The items of this factor are neglect household chores (SI1), incomplete in lessons (SI2), facilitates laziness (SI3), waste time (SI4) and conflict within family (SI5) with factor loading ranging from 0.495 to 0.693.

Factor 4 is addiction and comprise of four items. Factor 4 explains 5.111% of the variance in the data with an eigenvalue of 2.045. This factor consists of disfavor for hanging out with friends (AD1), disfavor for spending time with friends (AD2), dislike for watching TV(AD3) and rejection for doing sports (AD4) with factor loading ranging from 0.553 to 0.759.

Factor 5 is multiple uses and comprise of five items. Factor 5 explains 4.260% of the variance in the data with an eigenvalue of 1.704. The items of this factor are utilization for philanthropy (MU1), watching movie, drama series and funny videos (MU2), listening international songs and k-pop songs (MU3), playing game(MU4),conversation with friends and family(MU5) with factor loading ranging from 0.491 to 0.633.

Factor 6 is gratification and comprise of five items. Factor 6 explains 3.468% of the variance in the data with an eigenvalue of 1.387. This factor containseasy connection (GR1), development in opinions (GR2), advancement of knowledge (GR3), development in personal relationships (GR4) and updated with current affairs (GR5) with factor loading ranging from 0.438 to 0.637.

Factor 7 is health problem and comprise of four items. Factor 7 explains 3.145% of the variance in the data with an eigenvalue of 1.258. The items of this factor contain low gymnastics (HP1), physical problems (HP2), loss of appetite (HP3) and deprivation (HP4) with factor loading ranging from 0.555 to 0.737.

Factor 8 is personal uses and comprise of three items. Factor 8 explains 2.75% of the variance in the data with an eigenvalue of 1.1. The items of this factor are utilization for beauty and fashion (PS1), buying many articles in online shopping (PS2) and selling many articles in online shopping (PS3) with factor loading ranging from 0.481 to 0.788.

Table (4.3b)

Factor Analysis Results

Items	Estimated Factor Loadings								Communalities
	Factor								
	1	2	3	4	5	6	7	8	
Learning Utilization									
LU1	.721								0.586
LU2	.694								0.588
LU3	.650								0.54
LU4	.609								0.529
LU5	.568								0.526
LU6	.496								0.432
LU7	.458								0.357
Usable Place									
UP1		.753							0.637
UP2		.663							0.58
UP3		.652							0.523
UP4		.624							0.54
UP5		.472							0.364
UP6		.453							0.507
Destructive Effect									
DE1			.693						0.547
DE2			.643						0.484
DE3			.639						0.507
DE4			.625						0.521
DE5			.495						0.358
Addiction									
AD1				.759					0.634
AD2				.722					0.582
AD3				.641					0.521
AD4				.553					0.439

Source: Survey data

Table (4.3b)

Factor Analysis Results

Items	Estimated Factor Loadings								Communalities
	Factor								
	1	2	3	4	5	6	7	8	
Multiple Uses									
MU1					.633				0.459
MU2					.557				0.52
MU3					.550				0.415
MU4					.498				0.434
MU5					.491				0.491
Gratification									
GR1						.637			0.467
GR2						.486			0.477
GR3						.481			0.402
GR4						.476			0.454
GR5						.438			0.414
Health Problem									
HP1							.737		0.601
HP2							.680		0.605
HP3							.628		0.474
HP4							.555		0.419
Personal Uses									
PU1								.788	0.684
PU2								.765	0.649
PU3								.481	0.427

Source: Survey data

Table (4.3b)

Factor Analysis Results

Items	Estimated Factor Loadings							
	Factor							
	1	2	3	4	5	6	7	8
Eigenvalue	7.239	3.083	2.372	2.045	1.704	1.387	1.258	1.100
% of Variance	18.098	7.706	5.929	5.111	4.260	3.468	3.145	2.750
Cumulative % of Variance	18.098	25.805	31.734	36.845	41.105	44.573	47.718	50.468
Number of items (total=39)	7	6	5	4	5	5	4	3

Source: Survey data

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

4.4 Confirmatory Factor Analysis

The postulated factors of social media impact on students that were conducted by confirmatory factor analysis with structural equating model. Confirmatory factor analysis used to test a relationship between the observed variable and their underlying factors of social media usage and the effects of social media. The structural equation modeling (SEM) contains two inter-related models that are the measurement model and the structural model. Firstly, the skewness and kurtosis values of each factor and their standardized residual covariance matrix were examined for multivariate normality. For each variable, the skewness and kurtosis values ranged between -2 and +2. With the examination of standardized residual covariance matrix, residual values were less than 0.05 which were the indications of normality. Therefore, the overall variables satisfied multivariate normality distribution.

4.4.1 Measurement Model for the Factors of Social Media Usages

In measurement model, confirmatory factor analysis (CFA) was used to analyze that the factors (latent variables) are measured in terms of the observed variables and it describes the measurement properties of the observed variables. Confirmatory factor analysis for each factor is described in Table (4.4a). The parameters of model were estimated by maximum likelihood. As a result, the factor loads for all items are higher than 0.3. Factor loads of learning utilization accounts from 0.475 to 0.681. Factor loads for usable place accounts from 0.473 to 0.614. Factor loads of destructive effect accounts from 0.415 to 0.692. Factor loads for addiction accounts from 0.446 to 0.837. Factor loads for multiple uses accounts from 0.469 to 0.574 and that for gratification accounts from 0.485 to 0.605. Factor loads for health problem accounts from 0.525 to 0.693 and that for personal uses accounts from 0.41to 0.732.

Table (4.4a)

Confirmatory Factor Analysis Results for Each Factor

Factor (Latent Variable)	Indicator	Factor Loading	Residual (Error)	Composite Reliability
Learning Utilization	LU1	0.681	0.730	0.742
	LU2	0.626	0.770	
	LU3	0.542	1.062	
	LU4	0.639	0.703	
	LU5	0.616	0.766	
	LU6	0.552	0.834	
	LU7	0.475	1.071	
Usable Place	UP1	0.58	0.914	0.663
	UP2	0.473	1.085	
	UP3	0.605	0.866	
	UP4	0.614	0.934	
	UP5	0.511	1.021	
	UP6	0.575	0.916	

Source: Survey data

Table (4.4a)

Confirmatory Factor Analysis Results for Each Factor

Factor (Latent Variable)	Indicator	Factor Loading	Residual (Error)	Composite Reliability
Destructive effect	SI1	0.692	0.714	0.641
	SI2	0.543	0.964	
	SI3	0.623	0.822	
	SI4	0.63	0.807	
	SI5	0.415	1.405	
Addiction	AD1	0.837	0.408	0.638
	AD2	0.632	0.862	
	AD3	0.505	1.043	
	AD4	0.446	1.015	
Multiple Uses	MU1	0.513	0.905	0.61
	MU2	0.56	0.926	
	MU3	0.469	0.916	
	MU4	0.516	0.901	
	MU5	0.574	0.787	
Gratification	GR1	0.498	0.840	0.641
	GR2	0.605	0.868	
	GR3	0.485	0.902	
	GR4	0.577	0.818	
	GR5	0.573	0.778	
Health Problem	HP1	0.673	0.860	0.622
	HP2	0.693	0.230	
	HP3	0.537	0.903	
	HP4	0.525	0.997	

Source: Survey data

The goodness of fit criteria for the measurement model was analyzed to assess acceptable fit intervals for each factor and overall factors. Normed chi-square and the root mean square error of approximation were chosen as absolute fit indices. Goodness of fit index (GFI) which shows the amount of variances and covariance explained by the model. Comparative fit index (CFI) was determined as incremental fit index. Hu and Bentler (1999) stated that normed chi-square was less than6 and the root mean square error of approximation was less than0.8.Goodness of fit index (GFI) and comparative fit index (CFI) was greater than 0.8. The Standardized root mean square residual (SRMR) has chosen as adequate fit index. Schumacker and Lomax (2012) stated that the value of standardized root mean square residual has less than 0.08. The goodness of fit criteria for all factors is presented in Table (4.4b).

Table (4.4b)

Goodness of Fit Criteria for the Measurement Models

Model	Chi-Square	Degree Of freedom	Normed Chi-Square	GFI	CFI	RMSEA	SRMR
Learning Usage	48.732	14	3.481	0.976	0.959	0.067	0.036
Usage Place	22.631	8	2.829	0.986	0.976	0.058	0.028
Sad Impact	16.377	5	3.275	0.988	0.976	0.064	0.028
Addiction	4.304	1	4.304	0.996	0.992	0.078	0.016
Multiple Uses	6.47	5	1.294	0.995	0.995	0.023	0.02
Gratification	10.801	5	2.16	0.992	0.984	0.046	0.025
Health Problem	10.239	2	5.12	0.99	0.977	0.08	0.028
Personal Problem	0	0	0	1	1	0	0
Overall Factor	1444.46	671	2.153	0.878	0.85	0.046	0.055

Source: Survey data

In the results of absolute fit indices for each factor, normed chi- square values of eight factors and overall factors are from0 to 5.12. The values of root mean square error for eight factors and overall factors are from 0 to 0.078. Both normed chi-square and the root mean square error for eight factors are within acceptable limit. The goodness of fit indices (GFI) for each factor and overall factor ranged from 0.878 to 1 and the values for each factor are greater than 0.8. Therefore, the values of GFI for each factor are within acceptable fit. The comparative of fit (CFI) indices for each factor ranged from 0.85 to 1 and the values for each factor are greater than 0.8. Therefore, the values of each factor are within acceptable fit. The standardized root mean square residual for each factor and overall factor ranged from 0 to 0.055 and the values for each factor are less than 0.08. Therefore, the values of each factor are within acceptable fit. In addition, the composite reliability value was conducted for each factor. The values of each factor ranged from 0.606 to 0.742 and those are acceptable values.

4.4.2 Evaluation of Structural Model for the Effects and Usages of Social Media

The structural model is tested which includes hypotheses testing as regression weights analysis. The structural model defines the causal relationship among these latent variables (the arrows between the latent variables represent these structural connections).Because linear regression cannot test all relationships in a single statistical test, it is necessary to use the separate regressions to test the model fully. The structural model diagram was proposed by depending on the impact and usage of social media and is shown in figure (4.2).

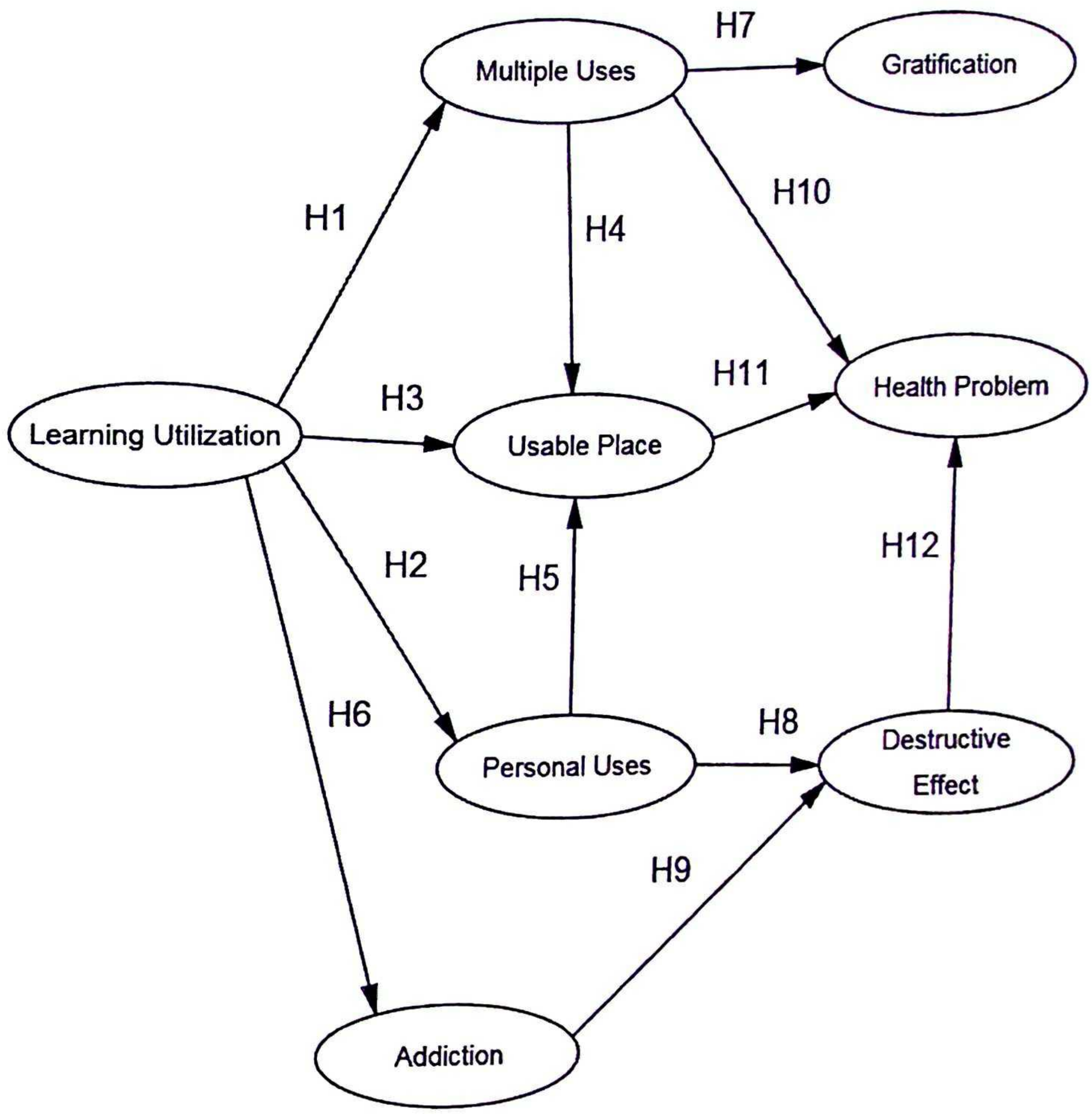

Figure (4.2) Structural Model Diagram for the Effects and Usages of Social Media

Actual Usages of Students

Actual usages of students measure the factors of social media usages that are the causes of utilization and usable place of social media. The structural equating model (SME) for social media actual usage of students is

$$MU = \alpha_1 LU + \varepsilon_1$$

$$PU = \alpha_2 LU + \varepsilon_2$$

$$UP = \alpha_3 LU + \varepsilon_3$$

$$UP = \alpha_4 PU + \varepsilon_3$$

$$UP = \alpha_5 MU + \varepsilon_3$$

where learning utilization (LP) is exogenous variable and usable place (UP) is both endogenous and exogenous variable. Multiple uses (MU) and personal uses (PU) are both endogenous and exogenous variables. Residuals of multiple uses, personal uses and usable place are ε_1,ε_2 andε_3.

Null Hypothesis:

H0: There is no causal relationship among the latent variables of social media actual usages on students.

Alternative Hypothesis:

H1: Social media usage for learning utilization has significant impact on social media usage for multiple uses.

H2: Social media usage for learning utilization has significant impact on social media usage for personal uses.

H3: Social media usage for learning utilization has significant impact on usable place for social media.

H4: Social media usage for personal uses has significant impact on usable place for social media.

H5: Social media usage for multiple uses has significant impact on usable place for social media.

Table (4.4c)

Standardized Regression Weights for Social Media Actual Usages of Students

Relationships of Factors			Regression Weights	Standard Error	Critical Ratio	P-value
Multiple Uses	<---	Learning Utilization	0.539	0.065	8.279	0.000
Personal Uses	<---	Learning Utilization	0.36	0.064	5.603	0.000
Usable Place	<---	Learning Utilization	-0.197	0.093	-2.111	0.035
Usable Place	<---	Personal Uses	0.279	0.06	4.676	0.000
Usable Place	<---	Multiple Uses	0.914	0.155	5.917	0.000

Source: Survey data

As results from Table (4.4c), the regression weighs was 0.539, 0.36, -0.197, 0.279 and 0.914 respectively and all of p-values is less than critical value (0.05). All regression weights were significant at 5% level. There is causal relationship among the latent variables of actual usages on students. Social media usages for learning utilization affect usable place for social media. Social media usages for multiple uses and personal uses affect learning utilization and usable place for social media.

Several Effects of Social Media in Students

The several effects of usages measure the effects of social media usages of students that are addiction, gratification and sad impact on social media. The structural equating model (SME) for effect of social media in students is

$$AD = \beta_1 LU + \varepsilon_4$$

$$GR = \beta_2 MU + \varepsilon_5$$

$$DE = \beta_3 PU + \varepsilon_6$$

$$UP = \beta_4 AD + \varepsilon_3$$

where learning utilization (LU) and gratification (GR) are exogenous variables. Destructive effect (DE) and usable place (UP) are also exogenous variables. Personal uses (PU) is endogenous. Addiction (AD) is both endogenous and exogenous variable. Multiple uses and personal uses are both endogenous and exogenous variables. Residuals of addiction, gratification, sad impact and usable place are ε_4,ε_5, ε_6 and ε_3.

Null Hypothesis:

H0: There is no causal relationship among the latent variables of social media impact on students.

Alternative Hypotheses:

H6: Social media usage for learning utilization has significant impact on addiction on social media.

H7: Gratification of social media has significant impact on social media usage for multiple uses.

H8: Social media usage for personal uses has significant impact on destructive effect of social media.

H9: Addiction on social media has significant impact on destructive effect of social media.

Table (4.4d)

Standardized Regression Weights for Effect of Social Media in Students

Relationships of Factors			Regression Weights	Standard Error	Critical Ratio	P-value
Addiction	<---	Learning Utilization	0.263	0.066	3.963	0.000
Gratification	<---	Multiple Uses	0.785	0.103	7.607	0.000
Sad Impact	<---	Personal Uses	0.337	0.063	5.367	0.000
Sad Impact	<---	Addiction	0.284	0.050	5.681	0.000

Source: Survey data

In the results from Table (4.4d), the regression weighs are 0.263, 0.785, 0.337 and 0.284 respectively and all of p-values are less than critical value (0.05). All regression weights are significant at 5% level. There is causal relationship among the latent variables of social media impact on students. Social media usages for learning utilization appear addiction on social media and social media usages for multiple uses obtain gratification of social media. Social media usages for personal uses appear destructive effect and destructive effect of social media occur health problem in students.

Health Effect on Students

Health effect of usages measure the interaction of health problem and social media uses of students. The structural equating model (SME) for heath effect of social media uses in students is

$$HP = \Upsilon_1 \text{ MU} + \varepsilon_7$$

$$HP = \Upsilon_2 \text{ PU} + \varepsilon_7$$

$$HP = \Upsilon_3 \text{UP} + \varepsilon_7$$

where health problem (HP) is endogenous variables. Multiple uses (MU), personal uses (PU) and usable place (UP) are exogenous variables and$\varepsilon_7$is the residual of health problem.

Null Hypothesis:

H0: There is no causal relationship among the latent variables of health effect on students.

Alternative Hypotheses:

H10: Social media usage for multiple uses has significant impact on health problem of students.

H11: Usable place for social media has significant impact on health problem of students.

H12: Destructive effect of social media has significant impact on health problem of students.

Table (4.4e)

Standardized Regression Weights for Health Effect on Students

Relationships of Factors			Regression Weights	Standard Error	Critical Ratio	P-value
Health Problem	<---	Multiple Uses	0.258	0.108	2.398	0.016
Health Problem	<---	Usable Place	0.183	0.083	2.197	0.028
Health Problem	<---	Destructive Effect	0.573	0.07	8.154	0.000

Source: Survey data

In the results from Table (4.4e), the regression weighs were 0.258, 0.183 and 0.573 respectively and all of p-values were less than critical value (0.05). All regression weights were significant at 5% level. There was causal relationship among the latent variables of health effect on students. Social media usage for multiple uses happen health effect of students. Usable place for social media and destructive effect happen health effect on students.

4.5 Comparing Means of the Selected Factors for Gender Groups

The mean of eight factors (learning utilization, usable place, sad impact, addiction, multiple uses, gratification, health problem and personal uses) was compared between gender groups. The two sample t-test or independent samples t-test was used to evaluate whether the mean value of the test variable for one group (male) differs significantly from the mean value of the test variable for the second group (female).With an independent samples t-test, each case must have scores on two variables, the grouping (independent) variable and the test (dependent) variable. The grouping variable divides cases into two mutually exclusive groups or categories, such as male or female for the grouping variable gender, while the test variable describes each case on some quantitative dimension such as test performance. The group means, t-statistic and p-value for the selected eight factors are presented in Table (4.5). The hypotheses for comparing means of the selected factors are

Null Hypothesis: The mean values of eight factors such as learning utilization, usable place, destructive effect, addiction, multiple uses, gratification, health problem and personal uses are not difference between gender groups.

Alternative Hypothesis: The mean values of eight factors such as learning utilization, usable place, destructive effect, addiction, multiple uses, gratification, health problem and personal uses are difference between gender groups.

Table (4.5)

Group Means and Independent Sample Test for the Selected Eight Factors

Variable	Group Means		t-value	P-value
	Male	Female		
Learning Utilization	0.0304	-0.0150	0.501	0.616
Usable Place	0.0416	-0.0206	0.685	0.493
Destructive Effect	0.1554	-0.0769	2.577	0.010
Addiction	-0.0538	0.0266	-0.888	0.375
Multiple Uses	0.1008	-0.0498	1.665	0.097
Gratification	0.1531	-0.0757	2.538	0.011
Health Problem	0.3086	-0.1526	5.210	0.000
Personal Uses	0.1326	-0.0656	2.194	0.029

According to Table (4.5), the value of t-statistic for learning utilization is 0.501 and p-value is 0.616. There has significantly difference between male students and female students at 5% level. Social media usage for learning utilization is difference in male students and female students. The value of t-statistic for usable place is 0.685 and p-value is 0.493. The usable place for social media is significantly difference between male students and female students at 5% level. The value of t-statistic for addiction is -0.888 and p-value is 0.375 and that for multiple uses is 1.665 and p-value was 0.097. At 5% level, there are significantly differences between male students and female students. The addiction on social media and social media usage for multiple uses are difference in male students and female students.

The values of t-statistic for destructive effect, gratification, health problem and personal uses are 2.577, 2.538, 5.210 and 2.194 respectively. The p-values for destructive effect, gratification, and personal uses are 0.01, 0.011, 0.029 and that for health problem is zero. There are not significantly difference between male students and female students at 5% level. Therefore, destructive effect and gratification of social media are not difference in male students and female students. Social media usage for personal uses is not different in male students and female students.

CHAPTER V

CONCLUSION

Internet technologies have a growing usage and most of social media influence people in Myanmar. According to the World Internet Statistics in 2017, there are about 13 million internet users, 25.1% population penetration and 11 million Facebook users in Myanmar. Social media are more influencing the university students and they have more impact of social media. Social media appear not only gratification and benefit but also social problem, addiction, social side effect and health problem on students. This thesis has focused the attitudes of social media usage among university students. The objective was to study better sense of how students' access and use social media during an average university day and assess the extent to which social media enhances or impacts on student's learning experiences.

The students of BAGO University were selected for research study and the students have been studied in June 2018. The design of survey has been based on the stratified random sampling. The students were grouped by educational level such as first year, second year, third year, fourth year and master. The sample size of students followed the distribution of total enrollment students in the academic year 2017-2018.

In this study, 33.1% of respondents are male students and 66.9% of respondents are female students. Almost 51.6% of the students aged between 19 and 21, 42.4% of the students aged between 16 and 18, and 6% of the respondents aged between 22 and 24. Almost 95% of the students use Facebook and Messenger and these social media is by far the favorite among students. Next, Viber and Google are the second and third popular of other social media. 87.64% of students use Viber and 72% of students use Google. 61.27% of students use YouTube, 43.09% and 37.7% of students use Instagram. Only 29.46% of students followed Twitter.

In factor analysis, 39 items of the effects of social media and social media usage among 40 items reduced to eight constructs: learning utilization, usable place, destructive effect, addiction, multiple uses, gratification, health problem and personal uses. Learning Utilization (Factor 1) contains seven items about social media usages for learning international language, discussion lesson, asking lesson, searching education information, reading online-book, sharing education knowledge and reading ism, admonishment and liters. Usable place (Factor 2) loads with six items. These items are social media uses place such as library, park, canteen, bus stop, leisure placement and wifi free place. Destructive effect (Factor 3) consists of five items that are the problem of social media usage. These items are neglect household chores, incomplete in lessons, facilitates laziness, waste time and conflict within family.

Addiction (Factor 4) includes four items that are preference in social media. These items are disfavor for hanging out with friends, disfavor for spending time with friends, dislike for watching TV and rejection for doing sports. Multiple Uses (Factor 5) consist of five items about the uses for philanthropy, watching movies, drama series and funny videos, listening international songs, playing games and the conversation with family and friends. Gratification (Factor 6) includes five items such as easy connection, developed in opinions, advancement of knowledge and development in personal relationships. Health problem (Factor 7) contains four items such as limitation on gymnastics, physical problem, loss of appetite and deprivation. Personal Uses (Factor 8) consist of three items such as social media uses for beauty and fashion, buying and selling in online shopping.

In the reliability analysis, the Cronbach's alpha of each factor is determined to test the reliability and internal consistency of each factor. The results of the alpha coefficients ranged 0.621 to 0.787 for the eight factors. The Cronbach's alpha reliability coefficient was calculated as 0.876 by examine the item-total statistics. The overall items have a high level of internal consistency. The results are reliable for accepting the reliability test.

Based on the KMO and Bartlett's Test, the factor analysis suitable to analyze the survey data since Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy was 0.861 and Bartlett's Test of Sphericity was 5956.019, which was significant at 1% level. From the eigenvalues and the scree plot, this trend is observed from the eight factors. Their eigenvalues are greater than 1and this first eight factors were obtained.

In confirmatory factor analysis, the each factor (learning utilization, usable place, destructive effect, addiction, multiple uses, gratification, health problem and personal uses) were tested to assess the relationship between the observed variables and their underlying factors of the effects of social media usages. The goodness of fit indices for each factor and overall factors ranged from 0.878 to 1 and the values for each factor and overall factors are greater than 0.8. Therefore, the variance and covariance of each factor and overall factor are from 87.8% to 100% explained by the model and that are fit acceptably. The comparative of fit indices for each factor and overall factor ranged from 0.85 to 1 and the values for each factor and overall factors are greater than 0.8. The standardized root mean square residual for each factor and overall factors ranged from 0 to 0.055 and the values for each factor and overall factors are less than 0.10. Therefore, the incremental fit values and the adequate fit values of each factor and overall factors are within acceptable fit. Next, the composite reliability values are conducted for each factor. The values of each factor ranged from 0.606 to 0.742 and that are acceptable values. It was found that the postulated eight factors by conducting the factor analysis are acceptable fit. Their models are fit acceptably.

Next, the effects and usages of social media have the causal relationships and interrelationship that are tested using the confirmatory factor analysis with structural equation modeling. All of the regression weights of the actual usages are significant at 5% level. The social media usages for learning utilization and multiples uses have a positive mutual effect and relationship on students. Moreover, the social media usage for learning utilization has the positive mutual effects and relationships on the social media usage for personal uses and the negative effect on the usable places for social media. The usable places for social media have positively the mutual effects and relationships on the social media usages for personal uses and multiples uses. Therefore, the personal and multiple usages are used by students in the usable places such as library, park, canteen, bus stop, leisure placement and wifi free places. Next, social media for learning utilization is not used by students in the usable places.

All regression weights of several effects are positively significant at 5% level. The social media usage for learning utilization is positively significant on addiction on social media. The social media usage for multiple uses is also positively significant on gratification of social media. Therefore, the addiction and gratification of social media affect students because social media is used for learning utilization and multiples uses. The personal uses and addiction are positively significant on destructive effect. Thus, the destructive effects of social media appear because social media is used for personal uses and students are addiction on social media.

All of the regression weights of health effect on students have a positively significant at 5% level. The social media usage for multiple uses, usable places of social media and destructive effect of social media have the positive significant on health problem of students. Therefore, social media usage and destructive effect of social media appear health problem of students.

Based on the survey results, the impact and usage of some social media factors were differences in male and female students. Also, the factors of social media have direct impacts on students. The eight factors of social media are correlated and the items of social media usage are correlated with each item. It is found that social media for learning utilization is not used by students in library, park, canteen, bus stop, leisure placement and wifi free place. At these places, students use social media for philanthropy, watching movies, drama series and funny videos, listening international songs and the conversation with family and friends, beauty and fashion, buying and selling in online shopping. They are favor in social media for educational learning and discussion, and searching education information and reading ism, admonishment, liters because there are positively interrelation between the learning utilization and addiction on social media. Students use the social media for philanthropy, watching movies, drama series and funny videos, listening international songs and the conversation with family and friends. Therefore they easy connect and develop in awareness, opinions, knowledge skills and personal relationships.

Also, the students are getting bored of housework and lessons, conflictwithin family and facilitate laziness because they are favor in social media and social media uses for beauty and fashion, buying and selling in online shopping and for philanthropy, watching movies, drama series and funny videos, listening international songs in usable places. Therefore, the students have health problem such limitation on gymnastics, physical problem, loss of appetite and deprivation.

The attitude and behavior of social media usage of students in BAGO University are studied in this study. Moreover, future studies could be applied in business sector, society and other aspect by using similar method of study so that a competitive analysis can be explored.

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APPENDICES

year

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	first year	205	37.3	37.3	37.3
	second year	149	27.1	27.1	64.4
	third year and first year (Hons)	111	20.2	20.2	84.5
	fourth year and second year (Hons)	74	13.5	13.5	98.0
	postgraduate	11	2.0	2.0	100.0
	Total	550	100.0	100.0	

gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	male	182	33.1	33.1	33.1
	female	368	66.9	66.9	100.0
	Total	550	100.0	100.0	

age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	16	11	2.0	2.0	2.0
	17	85	15.5	15.5	17.5
	18	157	28.5	28.5	46.0
	19	102	18.5	18.5	64.5
	20	102	18.5	18.5	83.1
	21	61	11.1	11.1	94.2
	22	20	3.6	3.6	97.8
	23	8	1.5	1.5	99.3
	24	4	.7	.7	100.0
	Total	550	100.0	100.0	

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.861
Bartlett's Test of Sphericity	Approx. Chi-Square	5956.019
	df	780
	Sig.	.000

Communalities

	Initial	Extraction
LU1	1.000	.586
LU2	1.000	.588
LU3	1.000	.540
LU4	1.000	.529
LU5	1.000	.526
LU6	1.000	.432
LU7	1.000	.357
LU8	1.000	.427
UP1	1.000	.637
UP2	1.000	.580
UP3	1.000	.523
UP4	1.000	.540
UP5	1.000	.364
UP6	1.000	.507
DE1	1.000	.547
DE2	1.000	.484
DE3	1.000	.507
DE4	1.000	.521
DE5	1.000	.358
AD1	1.000	.634
AD2	1.000	.582
AD3	1.000	.521
AD4	1.000	.439
MU1	1.000	.459
MU2	1.000	.520
MU3	1.000	.415
MU4	1.000	.434
MU5	1.000	.491
GR1	1.000	.467
GR2	1.000	.477
GR3	1.000	.402
GR4	1.000	.454
GR5	1.000	.414
HP1	1.000	.601
HP2	1.000	.605
HP3	1.000	.474
HP4	1.000	.419
PU1	1.000	.684
PU2	1.000	.649
PU3	1.000	.493

Extraction Method: Principal Component Analysis.

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.239	18.098	18.098	3.373	8.432	8.432
2	3.083	7.706	25.805	2.701	6.752	15.184
3	2.372	5.929	31.734	2.568	6.419	21.603
4	2.045	5.111	36.845	2.476	6.191	27.794
5	1.704	4.260	41.105	2.445	6.112	33.907
6	1.387	3.468	44.573	2.379	5.947	39.854
7	1.258	3.145	47.718	2.333	5.832	45.686
8	1.100	2.750	50.468	1.913	4.782	50.468
9	.984	2.460	52.929			
10	.960	2.401	55.329			
11	.927	2.318	57.647			
12	.906	2.265	59.912			
13	.878	2.196	62.108			
14	.836	2.091	64.198			
15	.827	2.067	66.265			
16	.799	1.999	68.264			
17	.744	1.860	70.124			
18	.727	1.818	71.943			
19	.700	1.750	73.693			
20	.681	1.702	75.394			
21	.667	1.666	77.061			
22	.646	1.614	78.675			
23	.638	1.595	80.269			
24	.622	1.555	81.824			
25	.597	1.493	83.317			
26	.592	1.481	84.798			
27	.560	1.401	86.199			
28	.547	1.367	87.565			
29	.526	1.316	88.881			
30	.488	1.221	90.102			
31	.464	1.160	91.262			
32	.446	1.114	92.377			
33	.441	1.102	93.479			
34	.431	1.076	94.555			
35	.409	1.023	95.578			
36	.399	.997	96.574			
37	.376	.940	97.514			
38	.349	.872	98.386			
39	.342	.855	99.241			
40	.304	.759	100.000			

Component Matrix[a]

	Component							
	1	2	3	4	5	6	7	8
UP6	.554			-.336				
GR2	.533		-.337					
LU5	.530	-.337						
MU5	.526							
LU6	.522							
LU2	.518	-.343						.347
GR5	.499							
MU2	.496					-.457		
LU1	.487	-.334	.407					
LU7	.481							
MU4	.472							
UP5	.470			-.335				
GR4	.463							
GR1	.460						.355	
MU1	.459						-.396	
LU8	.457							
LU4	.453	-.387						
MU3	.439							
HP1	.439				-.347	.391		
HP3	.407					.391		
GR3	.404						.349	
DE4	.375	.536						
DE1	.340	.508						
DE5		.480						
DE3	.351	.479						
DE2		.470						
HP4	.366	.372						
LU3	.366		.493					
AD3	.409		-.453					
PU1			.443		.436			-.401
PU3	.331		.409					
AD1	.353		-.398	.355				
AD4			-.391					
UP1	.444			-.494				.341
UP3	.414			-.487				
UP4	.407			-.467				
AD2				.443	.349			
UP2	.406			-.434				
PU2			.448		.471			
HP2	.414				-.450			

Extraction Method: Principal Component Analysis. a. 8 components extracted

Rotated Component Matrix[a]

	Component							
	1	2	3	4	5	6	7	8
LU1	.721							
LU2	.694							
LU3	.650							.334
LU4	.609							
LU5	.568					.417		
LU6	.496							
LU7	.458							
LU8	.358							
UP1		.753						
UP2		.663						
UP3		.652						
UP4		.624						
UP5		.472						
UP6		.453				.390		
DE1			.693					
DE2			.643					
DE3			.639					
DE4			.625					
DE5			.495					
AD1				.759				
AD2				.722				
AD3				.641				
AD4				.553				
MU1					.633			
MU2					.557			
MU3					.550			
MU4					.498			
MU5					.491			
GR1						.637		
GR2						.486		
GR3					.380	.481		
GR4				.340		.476		
GR5						.438		
HP1							.737	
HP2							.680	
HP3							.628	
HP4							.555	
PU1								.788
PU2								.765
PU3								.481

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 9 iterations.

Reliability Statistics

Cronbach's Alpha	N of Items
.787	7

Reliability Statistics

Cronbach's Alpha	N of Items
.746	6

Reliability Statistics

Cronbach's Alpha	N of Items
.713	5

Reliability Statistics

Cronbach's Alpha	N of Items
.714	4

Reliability Statistics

Cronbach's Alpha	N of Items
.654	5

Reliability Statistics

Cronbach's Alpha	N of Items
.682	5

Reliability Statistics

Cronbach's Alpha	N of Items
.699	4

Reliability Statistics

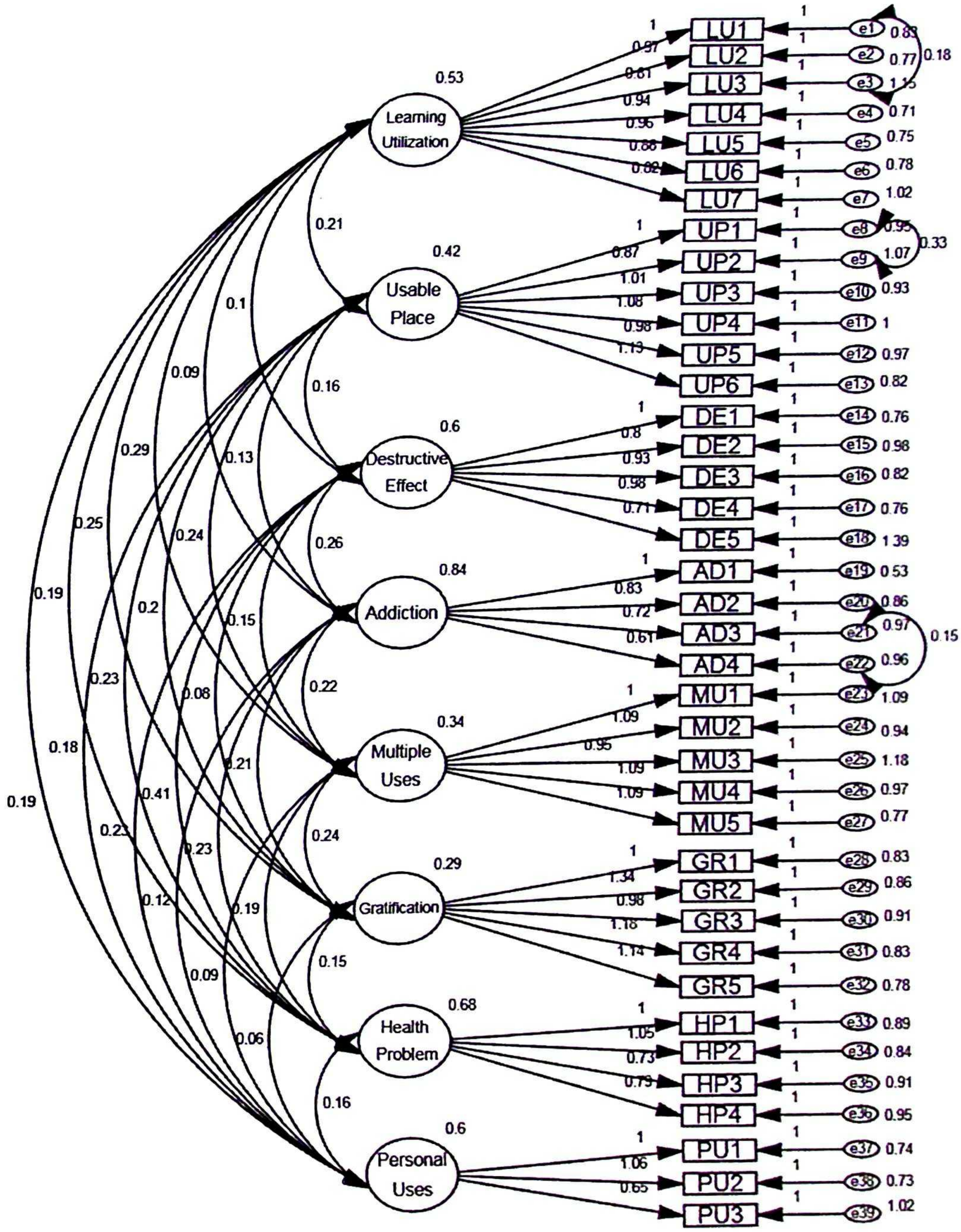
Cronbach's Alpha	N of Items
.621	3

Reliability Statistics

Cronbach's Alpha	N of Items
.879	40

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
LU1	125.53	360.101	.416	.876
LU2	125.50	359.942	.437	.875
LU3	125.85	363.722	.314	.877
LU4	125.48	363.378	.369	.876
LU5	125.28	359.627	.452	.875
LU6	125.32	360.569	.436	.875
LU7	125.54	360.356	.407	.876
LU8	125.41	361.993	.372	.876
UP1	125.83	360.685	.400	.876
UP2	126.03	362.041	.366	.876
UP3	125.51	362.835	.353	.877
UP4	125.69	362.008	.351	.877
UP5	125.43	360.092	.413	.876
UP6	125.34	357.056	.485	.874
DE1	126.16	363.619	.334	.877
DE2	126.18	366.253	.274	.878
DE3	126.06	363.249	.346	.877
DE4	126.04	362.222	.371	.876
DE5	126.57	367.503	.214	.880
AD1	126.29	363.393	.339	.877
AD2	126.12	366.680	.257	.878
AD3	125.78	362.131	.363	.877
AD4	125.85	365.647	.301	.878
MU1	125.58	360.628	.393	.876
MU2	125.46	359.777	.426	.875
MU3	125.59	360.551	.385	.876
MU4	125.44	361.270	.387	.876
MU5	125.22	360.008	.455	.875
GR1	125.39	363.350	.383	.876
GR2	125.43	358.115	.461	.875
GR3	125.50	365.055	.329	.877
GR4	125.50	362.243	.389	.876
GR5	125.44	361.426	.423	.876
HP1	125.69	359.271	.401	.876
HP2	125.73	359.967	.384	.876
HP3	125.83	362.766	.370	.876
HP4	125.91	363.224	.342	.877
PU1	126.35	364.865	.309	.877
PU2	126.72	367.326	.245	.879
PU3	126.07	365.664	.300	.878



Learning Utilization
Usable Place
Destructive Effect
Addiction
Multiple Uses
Gratification
Health Problem
Personal Uses
LU1
LU2
LU3
LU4
LU5
LU6
LU7
UP1
UP2
UP3
UP4
UP5
UP6
DE1
DE2
DE3
DE4
DE5
AD1
AD2
AD3
AD4
MU1
MU2
MU3
MU4
MU5
GR1
GR2
GR3
GR4
GR5
HP1
HP2
HP3
HP4
PU1
PU2
PU3

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	109	1444.461	671	.000	2.153
Saturated model	780	.000	0		
Independence model	39	5910.965	741	.000	7.977

RMR, GFI

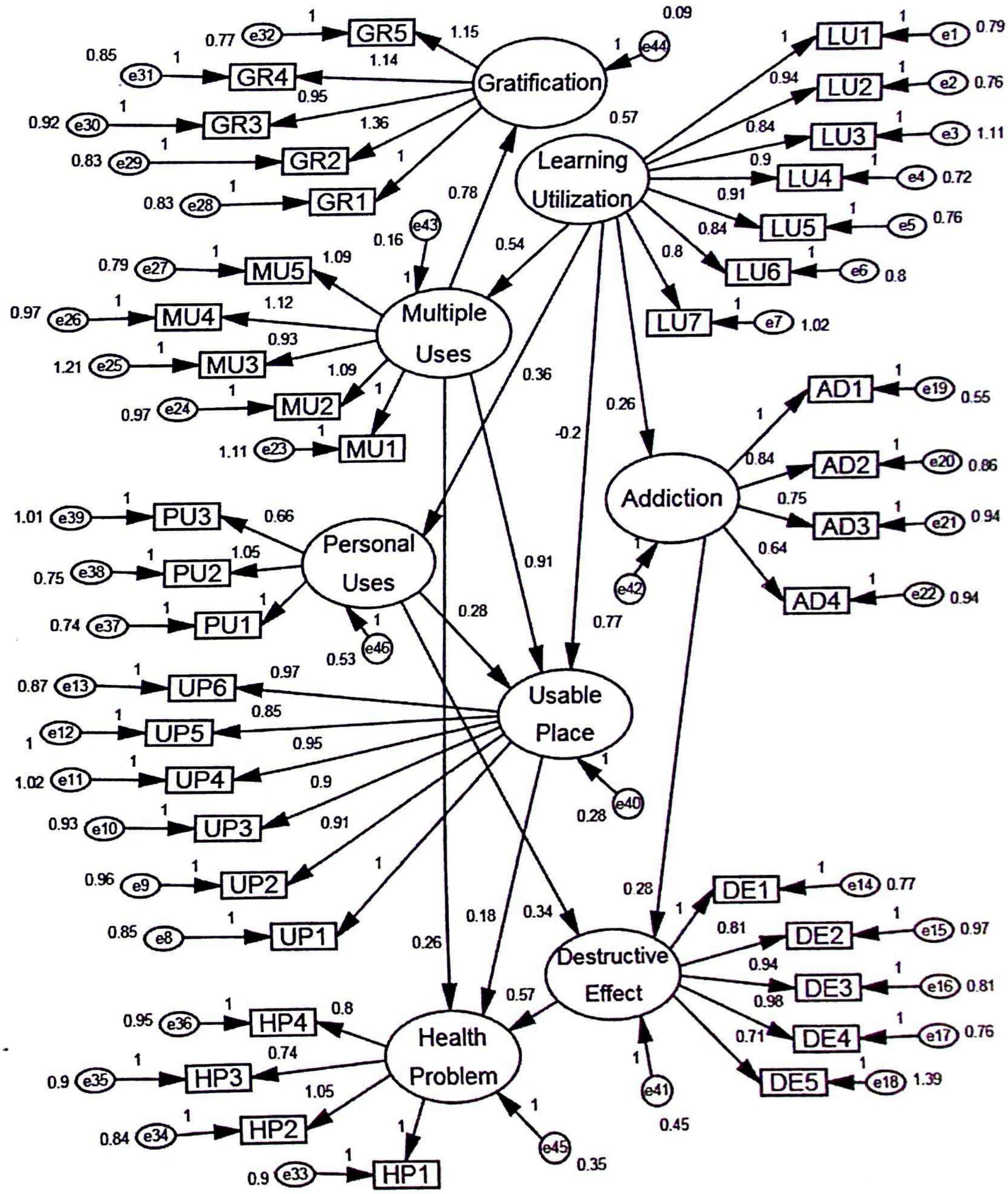
Model	RMR	GFI	AGFI	PGFI
Default model	.075	.878	.858	.755
Saturated model	.000	1.000		
Independence model	.241	.438	.408	.416

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.756	.730	.852	.835	.850
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.046	.043	.049	.983
Independence model	.113	.110	.115	.000



Gratification
Learning Utilization
Multiple Uses
Personal Uses
Addiction
Usable Place
Destructive Effect
Health Problem
GR5
GR4
GR3
GR2
GR1
LU1
LU2
LU3
LU4
LU5
LU6
LU7
MU5
MU4
MU3
MU2
MU1
AD1
AD2
AD3
AD4
PU3
PU2
PU1
UP6
UP5
UP4
UP3
UP2
UP1
DE1
DE2
DE3
DE4
DE5
HP4
HP3
HP2
HP1
e1
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e44
e45
e46
0.09
0.57
0.78
0.54
0.36
-0.2
0.26
0.16
0.91
0.28
0.77
0.53
0.28
0.28
0.18
0.34
0.26
0.57
0.45
0.35

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
REGR factor score 1 for analysis 1	Equal variances assumed	.045	.833	.501	548	.616	.04544652	.09068138	-.13267913	.22357217
	Equal variances not assumed			.505	369.032	.614	.04544652	.08990936	-.13135242	.22224546
REGR factor score 2 for analysis 1	Equal variances assumed	.173	.677	.685	548	.493	.06214741	.09066330	-.11594272	.24023755
	Equal variances not assumed			.686	361.867	.493	.06214741	.09056017	-.11594289	.24023771
REGR factor score 3 for analysis 1	Equal variances assumed	8.904	.003	2.577	548	.010	.23230265	.09015768	.05520571	.40939958
	Equal variances not assumed			2.792	446.013	.005	.23230265	.08319850	.06879289	.39581240

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
REGR factor score 4 for analysis 1	Equal variances assumed	2.470	.117	-.888	548	.375	-.08047521	.09063699	-.25851367	.09756324
	Equal variances not assumed			-.853	325.120	.394	-.08047521	.09436451	-.26611732	.10516689
REGR factor score 5 for analysis 1	Equal variances assumed	1.706	.192	1.665	548	.097	.15061272	.09047368	-.02710495	.32833039
	Equal variances not assumed			1.735	403.030	.083	.15061272	.08678547	-.01999601	.32122144
REGR factor score 6 for analysis 1	Equal variances assumed	2.583	.109	2.538	548	.011	.22887051	.09017369	.05174211	.40599891
	Equal variances not assumed			2.585	378.815	.010	.22887051	.08853024	.05479827	.40294275

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
REGR factor score 7 for analysis 1	Equal variances assumed	.234	.629	5.210	548	.000	.46126234	.08853603	.28735080	.63517387
	Equal variances not assumed			5.194	357.895	.000	.46126234	.08880671	.28661377	.63591090
REGR factor score 8 for analysis 1	Equal variances assumed	3.124	.078	2.194	548	.029	.19813882	.09030638	.02074980	.37552785
	Equal variances not assumed			2.325	420.982	.021	.19813882	.08521296	.03064294	.36563471

QUESTIONNAIRES

A STUDY OF SOCIAL MEDIA USAGE IMPACT ON UNIVERSITY STUDENTS

Name : ....

Major : ....

Year : ....

Gender : ....

Age : ....

Which social media you use the most?

....

Please indicate your answer. ■ (choose one)

1. ☐ Strongly Disagree 2. ☐ Disagree 3. ☐ Neither Agree nor Disagree

4. ☐ Agree 5. ☐ Strongly Agree

1. I use social media to learn international language.
   1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

2. I use social media to discuss lesson with my friends.
   1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

3. I use social media to ask/discuss lesson with my teachers.
   1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

4. I use social media to search education information.
   1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

5. I use social media to read online-book.
   1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

6. I use social media to share education knowledge.
   1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

7. I use social media to read ism, admonishment and liters.
   1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

8. I use social media for online teaching.
   1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

9. I use social media at library more than other place.
1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

10. I often use social media at the park more than other place.
1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

11. I use social media at canteen more than other place.
1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

12. I use social media at bus stop more than other place.
1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

13. I often use social media at leisure placement more than other area.
1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

14. I always use social media at Wifi free place more than other place.
1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

15. I often neglect household chores to spend more time on social media.
1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

16. I'm incomplete in my lessons by using social media.
1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

17. I feel bad if I am obliged to decrease the time I spend on social media.
1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

18. I feel that by using social media is idle away.
1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

19. Even my family frown upon, I cannot give up using social media.
1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

20. I prefer to use social media more than hanging with my friends.
1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

21. I prefer to use social media more than spending time with my friends.
1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

22. I prefer to use social media more than watching TV.
1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

23. I prefer to use social media more than doing sports.
1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

24. I use social media for philanthropy.
1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

25. I use social media for watching movie, drama series and funny videos.
1. ☐ 2. ☐ 3. ☐ 4. ☐ 5. ☐

26. I use social media to listen international songs and k-pop songs.
1.☐ 2.☐ 3.☐ 4.☐ 5.☐

27. I use social media to play game.
1.☐ 2.☐ 3.☐ 4.☐ 5.☐

28. I use social media to communicate the conversation with family and friends.
1.☐ 2.☐ 3.☐ 4.☐ 5.☐

29. I feel that using social media connect everywhere.
1.☐ 2.☐ 3.☐ 4.☐ 5.☐

30. I feel that my opinions have been developed by using social media.
1.☐ 2.☐ 3.☐ 4.☐ 5.☐

31. I feel that my knowledge skills have been advanced by using social media.
1.☐ 2.☐ 3.☐ 4.☐ 5.☐

32. I feel that my personal relationships have been developed by using social media.
1.☐ 2.☐ 3.☐ 4.☐ 5.☐

33. I feel that using social media makes it easy to know what's going on.
1.☐ 2.☐ 3.☐ 4.☐ 5.☐

34. I'm limited gymnastics due to use social media.
1.☐ 2.☐ 3.☐ 4.☐ 5.☐

35. Physical problems appear by spending social media.
1.☐ 2.☐ 3.☐ 4.☐ 5.☐

36. I feel that I am not hungry and thirsty when I am on social media.
1.☐ 2.☐ 3.☐ 4.☐ 5.☐

37. I feel deprivation due to use social media until midnight.
1.☐ 2.☐ 3.☐ 4.☐ 5.☐

38. I use social media for beauty and fashion.
1.☐ 2.☐ 3.☐ 4.☐ 5.☐

39. I use social media for articles to buy in online shopping.
1.☐ 2.☐ 3.☐ 4.☐ 5.☐

40. I use social media to sell for many articles in online shopping.
1.☐ 2.☐ 3.☐ 4.☐ 5.☐