YANGON UNIVERSITY OF ECONOMICS
DEPARTMENT OF STATISTICS

ADOPTION OF SOCIAL MEDIA USAGE AMONG STUDENTS IN YANGON UNIVERSITY OF ECONOMICS (YWAR THAR GYI CAMPUS)

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M.Econ (Statistics)
Roll No. 2

OCTOBER, 2023

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This thesis is submitted as a partial fulfillment towards the Degree of
Master of Economics (Statistics) Approved by the Board of Examiners

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This is to certify that this thesis entitled "**ADOPTION OF SOCIAL MEDIA USAGE AMONG STUDENTS IN YANGON UNIVERSITY OF ECONOMICS (YWAR THAR GYI CAMPUS)**"submitted as a partial fulfillment towards the requirements of Master of Economics (Statistics) has been accepted by the Board of Examiners.

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ABSTRACT

The social media usage has penetrated to the many areas in daily lives of today's students. This study aims to determine the influence of social media usage on the information behavior of undergraduate students in (Ywar Thar Gyi Campus) Yangon University of Economics. Simple random sampling method with probability proportional to size was used to collect data from 3047 students in this study. Descriptive Analysis, Confirmatory Factor Analysis and Structural Equation Modeling (SEM) are employed as the major statistical analytic techniques. The findings indicate that perceived usefulness and perceived ease of use have significantly positive effect on behavioral intention to use social media. Based on the results, the behavioral intention to use social media have significantly positive effect on actual usage of social media. Moreover, the social influence has significantly negative effect on behavioral intention to use social media. The study also found that the behavioral intention to use social media have significantly predict social media adoption. The results of the study might be helpful to students in their efforts to create initiatives to promote the usage of social media in blended learning classes and to increase social media adoption in academic purposes.

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LIST OF ABBREVATIONS

AGFI	Adjusted Goodness of fit index
ANOVA	Analysis of Variance
AU	Actual Use
AUS	Actual usage of Social media s (or) Behaviour Adoption of Social Media
AVE	Average Variance Extracted
B.Act	Bachelor of Accounting
B.Com	Bachelor of Commerce
B.Dev.S	Bachelor of Development Studies
B.Econ(Eco)	Bachelor of Economics
B.Econ(Stats)	Bachelor of Statistics
BBA	Bachelor of Business Administration
BBS	Bulletin Board System
BIN	Behavioral Intention to Use Social Media
BPA	Bachelor of Public Administration
BPS	Bachelor of Population Studies
CD	Coefficient of Determination
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CR	Convergent Validity
EFA	Exploratory Factor Analysis
GFI	Goodness of Fit Index
HEIs	Higher Education Institutions'
HOC	Higher-Order Components
ICT	Information and Communication Technologies
IRT	Item Response Theory
IU	Intention to Use
KMO	Kaiser-Meyer-Olkin
MIT	Massachusetts Institute of Technology
ML	Maximum Likelihood
NCA	Nationwide Ceasefire Agreement

NCI	Normed Chi-Square
NCP	Non-Centrality Parameter
NSF	National Science Foundation
PCA	Principal Component Analysis
PEOU	Perceived Ease of Use
PEU	Perceived Ease of Use
PLS	Partial Least Squares
PLS-SEM	Partial Least Squares-Structural Equation Modeling
PU	Perceived Usefulness
PUL	Perceived Usefulness
RMR	Root Mean Square Residual
RMSEA	Root Mean Square Error of Approximation
SE	Standard Errors
SEM	Structural Equation Modeling
SI	Social Influence
SMT	Social Media Technology
SNS	Social media ing Sites
SQRT	Square Root
SRMR	Standardized Root Mean Square Residual
TAM	Technology Acceptance Model
TED	Technology Entertainment Design
TLI	Tucker-Lewis Index
TOJDE	Turkish Online Journal of Distance Education
TRA	Theory of Reasoned Action
TRI	Technology Readiness Index
TV	Television
UTAUT	Unified Theory of Acceptance and Use of Technology
YTG	Ywar Thar Gyi
YUEco	Yangon University of Economics

CHAPTER I
INTRODUCTION

In today's society, social media is a term that everyone knows and all households with youngsters having access to the internet are familiar with multiple social media platforms exist currently. Recent years have witnessed a phenomenal proliferation and widespread use of social media platforms among a large population (Keane, 2018). Nowadays, younger people especially students in the universities all over the world are using social media. Therefore, it is necessary to explore the adoption and use of social media in an educational context.

1.1 Rationale of the Study

The 21st Century has been characterized with unprecedented increase in the technological advancement around the world. "Among these were advances in Internet facilities, establishment of libraries, development of information technology, and improvements in communications multimedia." Adeniyi (2004) established that everybody needs information to reach his or her potential and that the more information that is available to a 4 system about itself and about its environment the more reliable it becomes and the greater its chances of survival. On other hands, social media has become pervasive, playing a dominant role in the social structure of the society and changing the nature of social relationships. It has revolutionized the way communicate, interact and socialize. This new approach to consuming and creating information is in particular attractive to youths as a platform and space for activities not possible in the face-to-face context.

In this modern society, information behavior is a day-to-day activity that is essential to people in of all vocations and skilled occupations across various disciplines and professional groups. The proliferation of online social media has undoubtedly affected how students nowadays learn. Twenty first century learners, often considered critically engaged learners, are the technologically savvy students in today's classrooms. Being connected to social media sites such as Facebook, Twitter, Instagram, Pinterest, YouTube and many more throughout the course of their everyday activities (Rhoades, Friedel, & Irani, 2008).

The term information behavior is the currently preferred term used to describe ways in which human beings interact with information, in particular, the ways in which people seek and utilize information. In other words, information behavior covers a wide range of user behavior in relation to information and information systems, including information need generation, information creation, seeking, encountering, sharing, giving, assessment, management and use. These are studied in the context of different kinds of tasks in work, every day and play environments. All these aspects of information behavior can be studied in the context of social media use (Bates, 2010).

Among the vast variety of online tools which are available for communication, Social mediating Sites (SNS) have become the most modern and attractive tools for connecting people throughout the world. It is also about allowing people to connect with others just as it has been for many years. According to Khoo (2010), social media applications have influenced all areas and are having a major impact on how individuals live, work, play, learn and socialize. Social media in its various manifestations present a golden opportunity and rich environment to study information behavior, as much of the information (in text, image and video format) are recorded and stored in publicly accessible repositories and on personal devices.

Social media has increasingly influenced the information behavior of students in higher education over the past decade. It is a broad concept encompassing a wide range of Internet applications that support social interaction between individuals, with an emphasis on interaction between users, user-generated content and building of online relationships and communities. It is mainly used to promote the development of communication in society, ideas between people it's about sharing ideas and opinions (Turban, King & Lang, 2011). Among the users of social media are students who use social media tools for many purposes such as access to information, group discussion, resource sharing and entertainment (Wang, Chen & Liang, 2011). This has generated speculation on their use and related positive and negative implications, in both the short and long terms.

Social media is often lauded as a potentially transformative information resource. Information is the power house of the present emerging technological driven society. Today, information has been seen as heavily stressed factor that shapes the society. Information is a life blood of present society; it is accepted as a key issue in today’s viable world (Prabhavathi, 2011).

Information that is publicly available can be shared to enable people to perform various tasks in their private and official capacities. The need to make choices among several information sources leads to variations in people's information behavior. In judiciously making effective use of information, the society has exhibited a kind of behavior known as information behavior. Information behavior has been drastically transformed by the arrival of the internet and, in recent years, of social media. Just as it is known, new technologies help facilitate and provide flexibility in communicating and sharing of resources (Davies, 2012).

Social media plays a vital role in the sharing of information and is used to convey different types of information (i.e. sensitive, sensational, political and casual information) (Osatuyi, 2013). Over the last several years, information increased significantly in a large variety of formats. This information overload gave the foundation to the idea of studying the information searching or seeking behavior of users or human information behavior (Fasola & Olabode, 2013).

The expediency of accessing remote information through social media has resulted in tremendous popularity for web, which has given a new dimension to the library and information centers. In light of this, the job role and concept of library and librarians is dramatically changing with the application of information and communication technologies. The Internet has successfully entered all the areas and to a great extent is affecting the library and information centers. A wide range of public domain and commercial information sources are currently available on the internet such as bibliographical/ full text databases, table of contents of journals, discussion forums, technical reports, preprints, biographies, directories, data archives, teaching and training material, library catalogues, software etc. Furthermore, Internet use has become a way of life for the majority of higher education students all around the world. Social media support all kinds of social interactions, mediated and captured by Internet applications including mobile applications. The online communities that evolve exhibit social and collaborative information behavior that can be studied (Vijayakumar, 2015).

Social media technologies are enjoying a phenomenal success, Facebook, a social mediating website, claims that its active users reached 1.8 billion worldwide, more than 50% of which log in every day (Facebook, 2017). In the same vein, Twitter, a micro-blogging website hosts 317 million users who post on average 500 million tweets per day (Twitter, 2017). More than 1 billion unique users visit

YouTube each month, watching more than 6 billion hours of video (YouTube, 2017), and at the same time it is estimated that there are over 181 million blogs worldwide (Nielsen, 2012).

In fact, this kind of media has become Omni-present and a routine of life for millions of people worldwide. The overall social media research suggests that the encouragement motivation and satisfaction of students to utilize social media for purposes other than just social and networking activities. There has been an exceptionally rapid growth of social media, mainly owing to the technological factors like the availability of the broadband greater than before, the enhancement of software tools and the creation of more powerful computers and mobile devices. This study mainly aims at analyzing the adoptions of social media usage among students while they are studying.

1.2 Statement of the Problem

There is no doubt that social media has gained wider acceptability and usability and is also becoming probably the most important communication tools among students especially at the higher level of educational pursuit. However, it has been observed that the rate at which students use social media is critically affecting their information behavior either positively or negatively (Christopher, 2010). It is therefore evident that these studies were conducted on social media usage but focuses of those studies were mainly on adoption, utilization and challenges in using social media. However, there is more to explore in terms of influence of social media on information seeking behavior of university undergraduate students, particularly among undergraduate students in Yangon University of Economics (Ywar Thar Gyi Campus). In line with this proposition, this study seeks to investigate the adoption of social media usage on the information behavior of undergraduate students in Yangon University of Economics (Ywar Thar Gyi Campus).

1.3 Objectives of the Study

The main objective of the study is to investigate the adoption of social media among undergraduate students for the year 2023 at Yangon University of Economics (Ywar Thar Gyi Campus). The objectives specific of the study are:

1. To describe the social media usage of the university students.

2. To identify the factors that lead to social media usage of the university students.
3. To assess the causes and effects of social media actual usages of students in Yangon University of Economics.

1.4 Method of Study

In this study, primary data that is collected by Yangon University of Economics (Ywar Thar Gyi Campus). Quantitative survey is done by using the structured questionnaires, five points Likert-Scale on undergraduate students from YUEco (YTG Campus). Data were collected by face-to-face interview to the sample population. Simple random sampling method with probability proportional to size was used to find out the required sample size. Firstly, descriptive analysis was used to describe the social media usage of the university students. Secondly, Confirmatory Factor analysis was used to identify the factors that lead to social media usage of the university students. Finally, Structural Equation Modeling (SEM) was applied the causes and effects of social media actual usages of students in this study.

1.5 Scope and Limitations of the Study

Social media can be utilized various aspects of people and the many aspects of social media impacts on society. Among them, the adoption of social media usage on the information behavior of undergraduate students at Ywar Thar Gyi Campus in 2022-2023 academic year that has been analyzed by using the primary survey data. Data from personal interviews were analyzed to meet the objectives of the study. The quantitative response of 350 university students were analyzed in this study.

1.6 Organization of the Study

This study included five chapters. Chapter I is an introduction. It consists of the rationale of the study, statement of the problem, objectives of the study, the method of study, the scope and limitations of the study and the organization of the study. In Chapter II, the literature review is presented. The research methodology is described in Chapter III , Chapter IV is concerned with the results and findings of the study. Chapter V is the conclusion, findings and recommendations of the study.

CHAPTER II
LITERATURE REVIEW

This chapter reviews relevant literature for the study. It includes the literature review for this study, which is focused on the history of social media, the concept of social media, academic use of social media, social media usage by undergraduate students, review on related studies, the Technology Acceptance Model (TAM), and the conceptual framework of the study.

2.1 History of Social Media

To understand social media, it needs to explore its history. The Internet started out as a massive Bulletin Board System (BBS) that allowed users to exchange software, data, messages, and news with each other. In 1979, Duke University graduate students Tom Truscott and Jim Ellis teamed up with the idea of networked communication over computers for exchange of information. This idea was executed in 1980 and "Usenet" was launched worldwide, which was the first genuine attempt at social mediating. Various discussion groups were held covering a wide variety of topics from humanities, sciences, business, politics, computers, and other areas. The discussion forums on these websites were called "newsgroups" (Kaplan & Haenlein, 2010).

In 1992, Internet became one of the most popular networking tools, which linked researchers and educators. Marc Andreessen headed a team at NSF centers which successfully developed a browser to develop NCA Mosaic or popularly known as Mosaic. In less than 18 months of its introduction, Mosaic became the browser of choice for almost over a million users. This set off an exponential growth in the area of decentralizing information and connecting people and led to the development of Microsoft's Internet Explorer (Andreessen, 1993).

In 1999, social media websites like Blogger and Face Party appeared, and Post-2000, Wikipedia, Picasa, Friendster, Flickr and other sites were created. The social mediating site Facebook is currently one of the leaders in social media, with video sharing site YouTube a close second. Growth of social mediating, a revolution in social mediating came with the advent of newer social mediating websites, based on Web 2.0. In 2002, Friendster used the concept of degrees of separation. It promoted the idea of social mediating by creating rich bonds among people who knew each other directly or via certain friends and provided a common platform for them for social interaction. LinkedIn, launched in 2003, created a professional platform for work-based interaction. It is more than a mere playground for teenagers and classmates. LinkedIn is a serious platform for working people who want to connect with other professionals and to expand their contact networks.

However, Facebook, launched in 2004 for Harvard students and opened to the general public in 2006, is currently the most frequented social mediating website. As of September 2014, Facebook claims 1.35 billion active users (Calduch-Losa, 2018). To put this number in perspective, if Facebook was a country it would be the second most populous nation, second only to China. Like China and India, Facebook is an 'emerging' economy that business professionals are trying to understand. It has its own social norms, privacy issues, cultural sensitivities and community rules that govern how business is done and how its members engage and derive value.

2.2 Concept of Social Media

Over the years, many scholars have been able to distinctively define and clarify the concept of social media. In their definition and clarification, the concept of social media has been used interchangeably with social mediating site. Likewise, in this section, the word will be used interchangeably. Web 2.0 was 17 coined by Darcy DiNucci in 1999 to describe interactive social websites which allow users to interact and collaborate with each other in a social media dialogue. Social media provides active participation, connectivity, collaboration, and sharing of knowledge and ideas among users (McLoughlin & Lee, 2007). These benefits provided by social media are very relevant and necessary for educational context. For this reason, the research of social media use in education is an increasing topic among researchers. There are both qualitative and quantitative studies in the literature which investigate the relationship of social media and education.

According to Boyd & Ellison (2007), "social mediating sites are web-based service platform that enable individuals to create a public or semi-public profile within a bounded system, articulate a list of other users with whom they share a connection, and view and navigate their list of contacts and those made by others within the system". These sites are used to interact with friends, peers and others that are found in groups on these sites. The sharing of information ranges from news, debates, gossips, feelings or statement of mind, opinions, research etc.

According to Mayfield (2008), there are basically seven kinds of social media, including social medias, blogs, wikis, podcasts, forums, content communities and microblogging. In this study, the classification by Mayfield will be considered as the criterion in evaluating whether a platform belongs to social media or not.

Jantsch (2008) considered social media as the use of technology combined with social interaction to create or co-create value. Acknowledged social media as "the means for any person to: publish digital, creative content; provide and obtain real-time feedback via online discussions, commentary and evaluations; and incorporate changes or corrections to the original content" (Dykeman, 2008).

Drury (2008) described social media as online resources that people use to share content: video, photos, images, text, ideas, insight, humor, opinion, gossip, news. One thing that is common in the definitions of social media reviewed in this work is the view that it is based on user-generated participation.

The opportunity to enjoy user-to-user interaction distinguishes social media from the traditional media which is characterized by top-down news dissemination arrangement (Clark & Aufderheide, 2009). Another attribute of the social media which distinguishes it from the traditional media is the choice it accords its users. Choice enables people to access the information they like to learn about through the social media, eliminating the gatekeeper role of traditional media. On the one side, the choice offered by social media reduces the shared experience that viewers of particular traditional media channels usually have; on the other hand, it creates a network of individuals with like interests and similar preferences. Safko & Brake (2009) further defined social media as "activities, practices, and behaviors among communities of people who gather online to share information, knowledge, and opinions using conversational media.

Mangold & Faulds (2009) described social media more broadly. And then, social media can encompass every software program or website with which a person shares ideas, thoughts, pictures, audio, music, video and other content. They have subcategorized social media into fifteen different categories, which includes the following (Mangold & Faulds, 2009):

1. Social mediating sites (e.g. MySpace, Facebook, Faceparty)
2. Creative works sharing sites:

i. Video sharing sites (YouTube)
ii. Photo sharing sites (Flickr)
iii. Music sharing sites (Jamendo)
iv. Content sharing combined with assistance (Piczo)
v. General intellectual property sharing sites (Creative Commons)

3. User-sponsored blogs (Cnet.com)
4. Company sponsored websites/blogs (Apple Weblog)
5. Company-sponsored cause/help sites (click2quit.com)
6. Invitation-only social medias (ASmallWorld.net)
7. Business networking sites (LinkedIn)
8. Collaborative websites (Wikipedia)
9. Virtual Worlds (Second Life)
10. Commerce Communities (eBay, Amazon, Craigslist, iStockphoto)
11. Podcasts
12. News delivery sites (Current TV)
13. Educational material sharing (MIT Open Course Ware, TED)
14. Open Source Software communities (Linux, Mozilla)
15. Social bookmarking sites allowing users to recommend online news stories, music, videos etc.

In defining social media, Kaplan & Haenlein (2010) gave a general definition of social media in consideration of Web 2.0 and User-Generated Content. And then social media is a group of internet-based applications that build on the ideological and technological foundations of Web 2.0 and that allows the creation and exchange of User Generated Content. They also went further to describe social media as a group of internet-based applications that build on the ideological and technological foundations of Web 2.0 and that allow the creation and exchange of user-generated content.

Parr (2010) defined social media as the use of electronic and Internet tools for the purpose of sharing and discussing information and experiences with other human beings in more efficient ways. According to Andreas & Michael (2010), refers to "a group of Internet based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of user-generated content." The term social media, according to Kaplan & Haenlein (2010) "a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of user-generated content".

The scope of social mediating sites as information sources have been discussed by different scholars e.g., (Morris et al., 2010). They noted that:

i. Only humans can provide certain types of information such as opinions, advice and recommendations.
ii. The information sources are personally known to the user to a greater or lesser extent, and are therefore trusted sources and have cognitive authority.
iii. Users can provide localized (geographically specific) information, and current or time sensitive information.
iv. Information provided by users are customized for the requestor.
v. Social contacts can perform intermediary functions of researching, synthesis and packaging of information.
vi. Users are able to broadcast a question to a known group of people users can obtain emotional and social support.

It includes web-based and mobile based technologies that are used to turn communication into interactive dialogue among individuals, organizations, and communities. Typical examples of social media platforms include websites such as Facebook, Twitter, Flickr, YouTube and the interactive options on these websites, such as the “re-tweeting” option on Twitter. These instruments are referred to as media can also be used for the storage and dissemination of information. However, unlike the traditional media like Television and Radio, most of the social media tools allow their users to interact as “re–twitting” on Twitter and “comment” options on Facebook illustrate.

Bryer & Zavatarro (2011) described social media as technologies that smooth the progress of social interaction, make possible collaboration, and enable deliberation across stakeholders. These technologies now include blogs, wikis, media (audio, photo, video, text) sharing tools, networking platforms, and virtual worlds. Social Media Online (2011) defines social media as primarily internet-and mobile-based tools for sharing and discussing information by users. Social media, as defined by Bryer & Zavatarro (2011) are technologies that facilitate social interaction, make possible collaboration, and enable deliberation across stakeholders. These technologies now include blogs, wikis, media (Audio, photo, video, text) sharing tools, networking platforms, and virtual worlds. Curtis (2011) affirms that social media appear in many forms including blogs and microblogs, forums and message boards, social medias, wikis, virtual worlds, social bookmarking and video sharing.

Kietzmannn (2012) illustrated social media as the platform that employs mobile and web-based technology to create highly interactive platforms via which individuals and community share, co-create, discuss and modifies user generated content. Deil-Amen & Rios-Aguilar (2012) remit to social media technology (SMT) as web-based and mobile applications that allow individuals and organizations to create, engage, and share new user generated or existing content, in digital environments through multi-way communication. Through this platform, individuals and organizations create profiles, share and exchange information on various activities and interests. An interesting aspect of social media is that, it is not limited to desktop or laptop computers but could be accessed through mobile applications and smart phones making it very accessible and easy to use.

Different social media platforms were used to examine the effects of social media sites on education and collaborative work. The use of social media for educational purposes was analyzed also qualitatively by interviewing with university students and results showed that they use social media intensively for educational purposes such as exchanging practical and academic information, experiences, social support and also connecting with peers and sharing documents (Hrastinski & Aghaee, 2012).

Junco, et.al (2013) stated that there is a positive significant relationship between academic uses of information technology and the occurrences of collaborative learning, and also academic uses of technology increases the interaction between students and also student and faculty members. On the other hand, the study of Wiid & his colleagues (2013) indicated that the most important factors according to the students' perceptions that affect the use of social media as an effective lecturing tool are 'Ease of use' and 'Accessibility'. Nwanton (2013) defined social media as those internet-based tools and services that allow users to engage with each other, generate contents, distribute and search for information online.

Al-Rahmi (2014) also used two variables of Technology Acceptance Model which are "perceived ease of use" and "perceived usefulness" and with these variables they also use "engagement", "peer interaction" and "faculty interaction" as the predictors of collaborative learning. In addition, this study also investigates the effect of collaborative learning and student satisfaction. Finally, this study found that the effects of collaborative learning and student satisfaction on student's academic performance. All relations were found as significantly effective on indicated variables.

Chutwuere (2021), the factors that influence students' adopting social media platforms in their learning spaces are found in many information systems theories or models. The major theory is the Technology Acceptance Model (TAM), which presents several key adoption processes in accepting any given technological artifact. The ease of use, perceived usefulness, attitude, intention to use influence the perception of one using a technology. To this study, students' immediate perception of social media usage in education is dependent on its ease of use, perceived usefulness, attitude, intention to use, and others. These factors influence whether a student will adopt and use social media platforms to aid learning process. Nonetheless, perceived ease of use, and usefulness are the most influencing factors in adopting any technological artifact, including social media platforms in the learning environment.

To a greater extent, social media platform adoption is influenced by many key factors, including boredom, meeting friends, following a trend, entertainment, keeping in touch with friends, posting pictures, and others. However, students' adoption of social media platforms goes beyond self-entertainment and pressure; rather, it involves adding value to their learning career and progress. According to Murire & Cilliers, the factors influencing academia's adopting social media platforms can be tested on the Unified Theory of Acceptance and Use of Technology (UTAUST). The key components of UTAUST, which are "performance expectancy, effort expectancy, social influence, and facilitating conditions", can influence students or academia's adopting social media platforms in their teaching and learning environments.

Furthermore, students' adopting social media platforms in their learning environment can be influenced by the Technology Readiness Index (TRI). The components of TRI, such as optimism, innovativeness, discomfort, and insecurity, can influence students' adopting social media platforms in their learning environment.

Social media platforms are becoming a known channel in the higher education institutions' (HEIs) teaching and learning environment. Students are turning to social media platforms for their learning support and purposes. Social media platforms make learning easy because of their unique attributes: secure, interactive, economic, available, accessible, community-driven, reachable, creative, portable, user-based, and many more. Social media platforms are bidirectional because they allow for content or information flow between the content creator and reader believes that the Bidirectional flow of information and content on social media platforms makes it dynamic and exciting for the users.

Adopting social media platforms by students presents an enriched learning resource and opportunity to communicate in a new direction and participate actively in learning believe that social media platforms increase the pace for an immediate and futuristic learning environment and opportunities for students to share and interact with peers and experts.

Social media presents many opportunities and challenges for today's and future users. The challenges will impact students' academic performance and grading view that online users are challenged by interaction in a virtual environment. Students in developing countries are challenged in adopting social media platforms in their learning environment because of a lack of electricity, internet data, access to smartphones, or any internet-enabled phone. Students also lack the understanding that social media platforms can aid in their educational process and performance. All these and more bring challenges in adopting social media platforms for students in their learnings.

2.3 Academic Use of Social Media

The primary potentials of using social media to aid learning and teaching won't be fully achieved until there's a much better knowledge of the way the social character of those social media assets may be used to lure low engaged or disengaged students to have interaction in educationally purposeful ways using their high-engaged peers and teachers to ensure that it adds to the prosperity of a lot of students (Shoup & Gonyea, 2007).

Hamid (2009) stated that, the accessible literature consists of advantageous styles and designs of utilizing it at University level. It describes the development of contents and fewer focuses regarding how to share, interact, collaborate and socialize by its use. According to Chretien (2009), student's engagement signifies both time and effort students purchase educationally purposeful activities and indicates that because peers are extremely influential to student learning and values development, educational intuitions should make an effort to harness and shape this influence to ensure that it's educationally helping to strengthen academic anticipation.

Many scientists have addressed different regions of using social media networking at various academic and social levels. The advantages of social media designed for academic gains seem to become a market for a lot of scientists in education and social sciences. Mazman & Usluel (2010) described educational usage as an important benefit of social-networking sites. The portrayed Facebook, a popular social-networking site, as a useful educational tool due to its structure and various utilities, such as providing users with intentional or spontaneous learning opportunities by bringing people together around shared interests, exchanging information, sharing ideas, discussion topics and collaborating. Social medias are pedagogical tools because people can use them for connectivity and social support, collaborative information discovery and sharing, content creation, and knowledge and information aggregation and modification.

The accessible literature on social media submits helpful suggestions for applying in greater education. This clearly indicates that, the usage of social media by Students University is an interesting area of research for educationists and social scientists (Al-Rahmi & Othman, 2013).

2.4 Social Media Usage by Undergraduate Students

Schulten (2000) opined that student spend an average of 40 to 50 minutes a day surfing on Facebook. Gross (2004) noted that ‘‘students use social mediating sites not only for leisure and personal socialization but also as a platform for more meaningful and serious deliberations, and students are using social mediating for making friends, sharing links, online learning, finding jobs to accomplish their economic, educational, political and social being.’’

Wellens & Hooley (2009) conducted a study with first year undergraduates at a British university using an online survey. Students reported that they specifically joined Facebook pre-registration as a means of making new friends at university, as well as keeping in touch with friends and family at home. The survey data also reveal that once at university, Facebook was a social element that helped students settle into university life. Students thought Facebook was used most importantly for social reasons.

Liu (2010) studied students' use, attitudes and perceptions of 16 different social media tools through an online questionnaire involving 221 students. The top four reasons that prompted students' use of social media tools were found to be social engagement (85%), direct communications (56%), speed of feedback/ results (48%), and relationship building (47%).

According to Smith & Zickuhr (2010), about 57% of social media users are 18-29 years old and have a personal profile on multiple social media websites. The amount of time spent daily on social media sites varied greatly. However, an analysis of the data indicated most participants spent approximately 30 minutes a day socializing, mostly during the evening hours between 9 pm to 12 am. Students spent an average of 47 minutes a day on Facebook. More than 50% of college students go on a social mediating site several times a day.

Quan-Haase-Haas & Young (2010) found that 82% of college students reported logging into Facebook several times a day. Younger students tended to use Facebook more frequently than older students to keep in touch with friends from high school or from their hometown. Oluwatoyin (2011) stated that users of SNSs spend an average of two to six hours studying while non-users spent between eight and seventeen hours studying per week. Many students find that they actually spend 3 to 4 minutes during each visit to check updates, making several visits a day and others spend 8 hours a day on the website (Rouis, Limayen & Sangari, 2011).

Ahmed & Qazi (2011) argued that students manage their time efficiently and fulfill their study requirements effectively; hence, use of SNSs does not have an adverse impact on their academic performance. In the study conducted at St. Cloud State University in Minnesota, both males and females, time spent on SNS decreased as the age of the respondent increased and results revealed that female college students spent more time on SNSs than male students.

Bolong & Osman (2011) was conducted to identify the relationship between female students' motives for Facebook use and Facebook addiction. The five motives established were social interaction, passing time, entertainment, companionship, and communication. The findings of the study showed that there is significant relationship between female students' motives for Facebook use and Facebook addiction. The research concluded that the five motives established were among the major contributors to the addiction of Facebook.

Wang, et. al (2011) reported that most college students spent vast number of hours accessing social media sites. Ninety percent of students surveyed spent their time on entertainment. While eighty percent of the sample admitted that they posted or responded while completing homework, not too many college students preferred using social media to do their homework. Considering the overall results of collected data analysis, there was a negative attitude towards social media when college students used them. The analysis also indicates that an approach is needed to better balance the relationship between social media and academic study.

According to the study done by Manjunatha (2013), 80 percent of the students spending considerable amount of time on using social networking sites (SNS) regularly. Majority of Indian college students (62.6%) spent up to 10 hours per week of their time on using social mediating and reportedly 17.5% of students spent more than 10 hours per week.

In a study conducted by Camilia, Ibrahim & Dalhatu (2013) on the effect of social mediating sites usage on the studies of Nigerian students, the study revealed that 51% of respondents use the SNS to keep in touch with friends and family members, 28% use it to while away time, 5% of the respondents say they use the SNS just to belong while 16% use it to solve their social problems.

Singh & Kumar (2013) conducted that a study to measure the usage of social mediating among their research students. The findings of the study show that majority of the respondents were found to be aware and making use of social media in their research work. Their study also reveals that Facebook is the most popular social mediating sites among the research scholars.

Choi & Kang (2014) examined the students' motive of using social media in their learning process. 1010 students participated in the study and data were collected using online survey. The findings indicated that 71.2% of the respondents used social media to solve assignments with friends, 75.5% to search information, 49.3% to ask questions, 61.4% to publish contents, 39.4% to receive feedback and 44.5% to revise, edit and republish information.

Hashim & Kutbi (2015) found that American youths spend average 3.8 hours a day on social mediating from a computer, mobile phone and/ or tablet. Social media represents useful tools for communication and education, and provides an opportunity for networking in any profession. With time constraints and demanding class schedules, social media helps students to multitask because they do not want to spend time creating multiple individual messages.

Idubor (2015) investigated social media usage and addiction levels among undergraduates in University of Ibadan, Nigeria. The study revealed that majority of the respondents attested to making friends 651 (78.2%), getting news 566 (67.9%), communication 554 (66.5%) and online learning 450 (54.0%) as the major purposes for which they make use of social media networks. This implies that undergraduate students in University of Ibadan make use of social media network mainly for the purposes of making friends, getting news, communication and online learning.

2.5 Review on Related Studies

Boateng (2016) explored that ‘social media adoption among university students to examine the effect of perceived usefulness, perceived ease of use and gender on social media adoption. The respondents were mostly youth and were selected using convenience sampling technique. The findings indicate that, perceived usefulness and perceived ease of use significantly predict social media adoption. However, there is no significant difference between males and females on adoption of social media. The implications of the results for the youth, teachers, technologist, marketers and developers of information systems have been put forward.

Fernandez (2017) pointed out analysis of the use of social media in Higher Education Institutions (HEIs) using the Technology Acceptance Model understanding of the drivers of social media in Higher Education Institutions (HEIs) in an emerging economy. This research adopts the Technology Acceptance Model but included subjective norm, perceived playfulness, internet reliability and speed as additional constructs. With these inclusions, the model is appropriate and relevant in explaining users’ adoption and usage behavior of social media. The Principal Component Analysis (PCA) and Structural Equation Modeling (SEM) in analyzing the complex relationships between determinants of these technologies. The research demonstrated that perceived usefulness, perceived ease of use, subjective norm, and perceived playfulness (happiness) are robust predictors of usage behavior of students. The analysis between public and private HEIs undertaken here extends our understanding towards the different behaviors of users. The findings, though preliminary, suggest that private HEIs should initiate or continue the use of social media in classrooms, because intention to use translate to actual use of these tools. Public institutions, however, should improve Internet reliability and speed and should reassess their use of social media in order to fully take advantage of the benefits of ICT.

Adeboye (2017) studied that statistical effects of social media and ICT on the academic performance: an application of principal component analysis. This study to identify most prevalent factors responsible for the negative and positive effects of ICT influenced of social media on student academic performance with the aid of Principal Component Analysis. The results revealed that two of the factors, social media allow easy exchange of information with peers and social media facilitate smooth interaction with the lecturers are the most prevalent with cumulative variance of 59.21%. These effects are found to be positive on student's academic performance with respective eigenvalues of 1.82 and 1.4.

Bozanta (2017) examined that the effects of social media use on collaborative learning: a case of turkey. This study aims to determine the effects of social media on collaborative learning. Structural equation modelling is employed as the major statistical analytic technique. The findings indicate that perceived ease of use is a predictor of perceived usefulness and both of these have impact on social media use of students for educational purposes. Social media usage improves peer interaction and course engagement of students and also students' interaction with faculty members. The results of the study might be helpful to students and educational leaders in their efforts to create initiatives to support, promote, and encourage the implementation and usage of social media in blended learning classes and provide adequate training for teachers to increase social media adoption.

Mowafy (2018) investigated that the effects of social media on the academic performance of Nile University Students. This study examines the role of social media in students' academic endeavors and ultimately their academic performance through their reported perceptions and reflections. It also examines factors that might influence the nature of this relationship, and its tentative impact on the academic performance of Nile University undergraduate students. This model using descriptive and inferential statistical tests based on the research question and the nature of the data to be analyzed using frequency tables, crosstabs, ANOVAs, post HOCs and t-tests. The findings of the study significant differences in the behavior of students from different academic majors and different academic status in perceiving and using social media emerged which might require further investigation.

Salloum, et. al (2018) studied that as the number of university students using social media increases, the interest in assessing the adoption of social media applications and the factors encouraging it whether inside or outside classrooms has also risen. This study aims at exploring these educational outcomes and assessing a research model of antecedents and the cost of social media use. It also determines the factors of implementing social networking media for e-learning in the United Arab

Emirates higher education institutions utilizing the Technology Acceptance Model (TAM) which stresses the Perceived Ease of Use and Perceived Usefulness along with the Behavior Intention to use social networking media. The quantitative response of 408 university students embedding social media in their teaching methods was analyzed. To predict an Emirati student's behavioral intention to use social networking media for e-learning, a partial least squares (PLS) analysis points out that Perceived Ease of Use and Perceived Usefulness are important factors. Accordingly, the proposed model in this study illustrates the ways social media educational use positively influences efficient performances in the classroom.

Abrahim (2019) applied the structural equation modelling and confirmatory factor analysis of social media use and education. This study seeks to examine the attitude, perception and behavior of Japanese students towards social-networking sites, and how students from non-English speaking backgrounds (especially Japanese students) at the University of Toyama perceive the use of Facebook for learning English as a foreign language. The results of the proposed model confirmed the hypothesized latent structures and theoretical validity of probed factors. Conclusions drawn from this study might be useful to better understand the use of social mediating tools in educational context.

Yahaya (2019) analyzed that Influence of Social Media Usage on the Information Behavior of Undergraduate Students in Selected Universities in Kwara State, Nigeria investigated that the influence of social media usage on the information behavior of undergraduate students in selected universities in Kwara State, Nigeria. The study adopted descriptive survey research design. The population for this study comprised of undergraduate students in Al-Hikmah University, Kwara State University and University of Ilorin. Israel (2003) sample size model was used to calculate the sample size with precision levels of 5% and confidence level of 95% and the recommended sample size was three hundred and eighty-five (385). The findings of the study show Facebook as the most preferred social media tools by undergraduate students. The findings further revealed that there is a high usage of social media among undergraduate students. The findings also showed that the major purposes of using social media by undergraduate students are to connect with friends and for academic activities.

Pokhrel (2022) examined that intention of social media adoption among undergraduate students of business schools in Kathmandu valley. Data were analyzed by applying Partial Least Squares-Structural Equation Modeling (PLS-SEM). This study found a significant positive influence of resource sharing on behavior intention of social media adoption. The hypothesis showed that perceived ease of use partially mediated the relationship between collaboration and behavior of educational use of social media. However, the study found no significant influence of perceived ease of use, and perceived usefulness on behavior intention of social media adoption.

Mangden (2023) described that Effects of Social Media on Students' Academic Performance in Nigerian Universities: The study that acquiring information both locally and internationally is no longer a struggle as compared to the olden days. Most students used social media to collaborate with one another on assignments and lecture notes which further enhanced their ability to use social mediating sites for improved academic performance. The findings revealed that the internet was used to connect with other people for academic or commercial purposes; it also indicated that students use different social media on daily basis for different purposes which also served as a distraction.

2.6 Technology Acceptance Model (TAM)

TAM assumes an individual's intent to use a newly developed system, or technology's influences on their actual behavior. The TAM was developed based on theories such as expectancy theory, self-efficacy theory, cost-benefit paradigm from perspective of behavior decision making, and diffusion of innovations theory. Davis & Venkatesh (1996) describe TAM as a model for predicting users' acceptance and behavior in information systems. Perceived usefulness (PUL) and perceived ease of use (PEU) of social media have significant effects on adoption intentions, Davis (1986).

Davis (1986) developed the TAM (Figure. 2.1), which is based on the Theory of Reasoned Action (TRA), to understand the causal relationships among users' internal beliefs, attitudes, and intentions as well as to predict and explain acceptance of computer technology. This model posits that the user's actual usage behavior (actual use or AUS) is directly affected by behavioral intention (intention to use or IU). In turn, behavioral intention is determined by both the user's attitude and its perception of usefulness. The user's attitude is considered to be significantly influenced by two key beliefs, perceived usefulness (PUL) and perceived ease of use (PEOU), and that these beliefs act as mediators between external variables (e.g.

design features, prior usage and experience, computer self-efficacy, and confidence in technology) and intention to use. Furthermore, TAM theorizes that PEOU indirectly affects IU through PUL (Davis et al., 1989; Venkatesh & Davis, 2000).

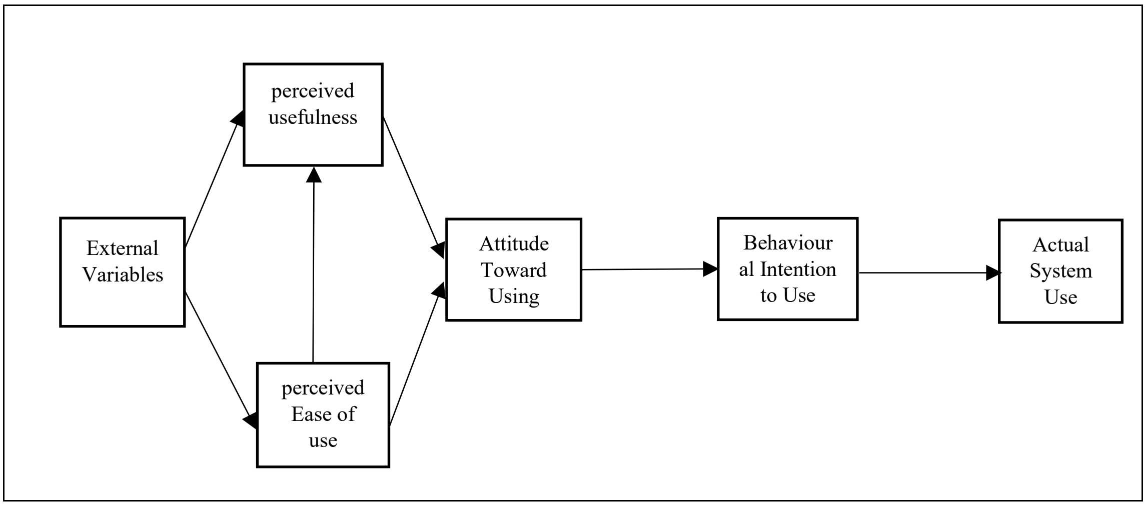

Figure 2.1 Technology Acceptance Model (TAM)

Source: Davis (1986)

2.7 Conceptual Framework of the Study

The current study aims to create a framework that focuses on the connection between e-learning and social media use among university-level students by applying the Technology Acceptance Model (TAM) about United Arab Emirates higher education institutions. The factors analyzed in this study are presented in Table 2.1 along with their operational definitions and related studies. Based on the research design, six hypotheses were made and evaluated in the present study.

Table 2.1 Operational Definition of Variables

Factors	Operational definition
Social Influence	The degree to which an individual perceives that important others believe students should use the new system.
Perceived Usefulness	The degree to which people believe that using particular technology improves student's job performance.
Perceived Ease of use	When a person believes that the user of technology uses little effort.
Behavioral Intention to use Social Media	An intention of an individual to perform in a specific way toward someone or something.
Behavior adoption of social media (or) Actual Usage of Social Media	The behavior adoption of social media or actual use of social media is the amount of time employed by users.

Source: (Davis, 1989)

The social influence as the degree where a person understands how others believe that a new information system should be implemented by students is described in (Venkatesh et al., 2003). A person's intentions for adopting new technologies are developed through social influence. The effect of perceived usefulness and behavioral intention to use social media (BIN) is concluded in the hypotheses of social influence (SI) will have a positive effect on perceived usefulness (PUL). And then, this study was tested social influence (SI) will have a positive effect on behavioral intention to use social media technology (BIN).

The perceived usefulness of a system is defined as the degree to which a person believes it will improve student's performance (Davis, 1989). In the social media context, perceived usefulness refers to the degree to which an individual believes that using Facebook for education PUL purposes would enhance students' performance. In the TAM, studies showed that perceived usefulness has a significant positive effect on behavior intention of technology acceptance (Davis, 1989). Zulfiqar et al. (2018) reported a significant effect of perceived usefulness on behavior intention related to social media use in an educational context. This study hypothesized that; perceived usefulness positively influences behavioral intention to use social media (BIN).

Perceived ease of use refers to the degree to which a person believes that using a particular system would be free of effort. In the social media context, perceived ease of use refers to the degree to which an individual believes that using Facebook for education purposes would be free of effort. Using the TAM, studies showed that perceived ease of use significantly impacted behavioral intention of technology acceptance (Davis, 1989). In an educational context, Zulfiqar et al. (2018) found a positive effect of perceived ease of use on social media adoption intentions. Likewise, Rahman et al. (2020) showed that perceived usefulness significantly affected behavior intention among undergraduates. Thus, this study hypothesized that a significant positive connection amongst behavioral intention to use social media (BIN), perceived usefulness (PUL) and perceived ease of use (PEU).

The general perception of behavioral intention is that it's a part of an attitude. An intention of an individual to react in a particular way towards someone or something is termed a behavioral intention (Robbbins, 2005). The behavioral intention to a direct and significant use affects the actual system use (AUS) of social media technology as indicated by various studies. This study hypothesized that; the behavioral intention to use (BIN) will have a positive effect on the actual use of social media (AUS).

The Figure 2.2 illustrates the conceptual framework model developed based on the above concepts, which considers an extended TAM model for the adoption or acceptance of social media usage among students.

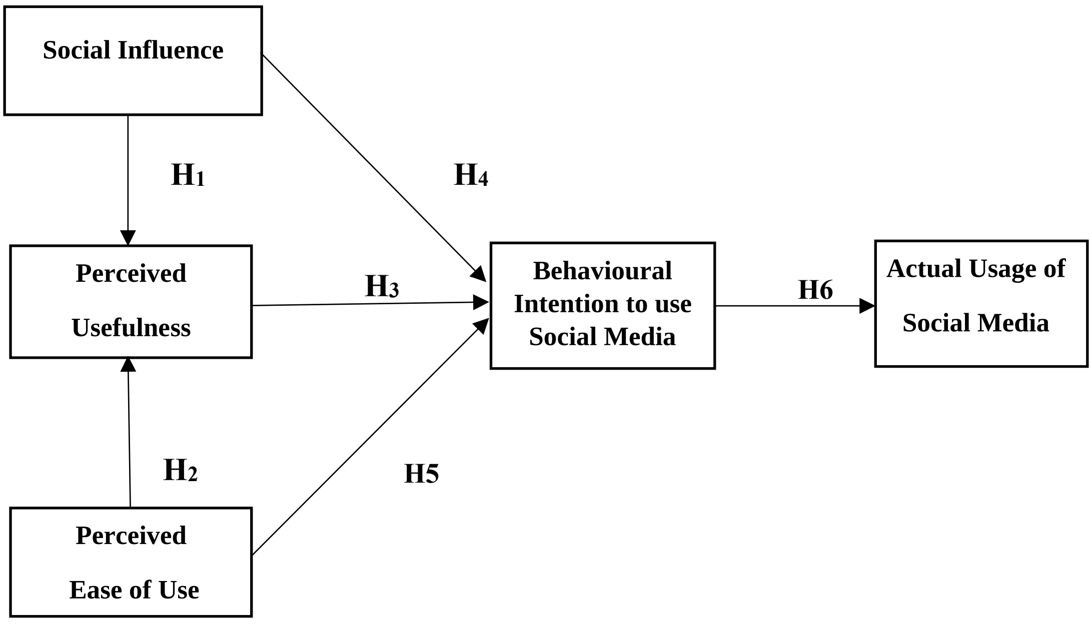

Figure 2.2 Conceptual Framework of the Study

Source: Author's Own Compilations

CHAPTER III
RESEARCH METHODOLOGY

This chapter contains the general procedure for the conduct of the study. It therefore gives detail information on the following: research design, population of the study, sampling techniques and required sample size, data collection instrument, and method of data analysis.

3.1 Research Design

A research design is a framework for conducting the research project. It specifies the details of the procedures necessary for obtaining the information need for the study. Therefore, research design of the study includes the research population and sampling, data collection methods, and the research techniques employed for data analysis. It is the overall plan for connecting the conceptual research problems. In other words, the research design sets the procedure on the required data, the methods to be applied to collect and analyze of the data, and how all of this is going to answer the research question. It has used separate procedures for the quantitative and qualitative approaches purpose to serve. Furthermore, the approaches implemented to enhance the validity and reliability of the studies are also explained in detail.

3.2 Population of the Study

The research population is described as the entire group of people on whom the results of a study are intended to be applied (Johnson & Christensen, 2012). The study is being undertaken to examine the adoption of social media usage among students in Yangon University of Economics (Ywar Thar Gyi Campus). According to the data collected through from the Student Affairs Department in (Ywar Thar Gyi Campus), Yangon University of Economics. The population of undergraduate students are 3047 in 2022-2023 academic year.

3.3 Sampling Technique and Sample Size

Sampling technique is the approach used in taking a small group from a larger group, investigate it, and draw an accurate conclusion that can be generalized onto the larger group (Rea & Parker, 2005).

This study adopts simple random sampling technique to select undergraduate students in Yangon University of Economics (Ywar Thar Gyi Campus). According to Aina (2002), simple random sampling is the basic sampling method of survey research and it aims at giving each person in the sampling frame an equal chance of being selected in the sample. Thus, the sample size comprises of the portion of the population for the study. This ensures that samples are representative to enable generalization of the population.

In order to accurately take a sample from the population, the Yamane's sample size formula was used to determine the sample size. The formula states that, a given total population of N, if ± 5% is taken for precision levels where the confidence level is 95% and p = 0.5, the sample (n). Based on Yamane (1973) sample size formula, the total population is 3047; by taken ± 5%, the expected sample size should be 350.

Sample Size Determination

To determine the size of sample, formula developed by Yamane (1973) for categorical data is as follows.

To be more accurate Yamane (1973) adjusted calculation formula was used by increasing p = proportion of students who actual use of social media is equal to 0.50 and z = 1.96 score at significance α = 0.05.

$$n = \frac{(z)^2(p)(1-p)(N)}{(z)^2(p)(1-p)+(N)(e)^2}$$

where, n = sample size

N = population size

e = margin of error (0.05) reliability level 95%

$$n = \frac{(1.96)^2(0.5)(1-0.5)(3047)}{(1.96)^2(0.5)(1-0.5)+(3047)(0.05)^2}$$

$$= 341.15 \approx 342$$

Therefore, the required sample size is obtained as at least 342. Approximately 350 respondents are randomly chosen from (Ywar Thar Gyi Campus) 3047 by simple random sampling method with probability proportional to size. Taking a random sample of 350 respondents are shown in Table 3.1.

Table 3.1 List of Selected Respondents in YUEco (YTG Campus)

Years of Attendance	**Number of Respondents**	**Number of Sample Respondents**
First year	1124	129
Second year (First semester)	466	54
Second year (Second semester)	426	49
Third year/ H_1	452	52
Final year/ H_2/ H_3 and Qualified	579	66
Total	**3047**	**350**

Source: Survey Data (2023)

3.4 Data Collection Instrument

According to Kiplang'at & Ocholla (2005) data collection instruments are expected to provide accurate and adequate data in line with the objectives of the study. For this study, questionnaire titled "Adoption of Social Media Usage Among Students in Yangon University of Economics (Ywar Thar Gyi Campus) Questionnaire" was used as the data collection instrument. The questionnaire was developed by the researcher in accordance to the research objectives.

The questionnaire was divided into three sections. Section A of the questionnaire focused on the demographic information of the respondents. Section B of the questionnaire focused on identifying the social media tools used by undergraduate students. Section C of the questionnaire which is to determine the extent of social media utilization by undergraduate students was divided into five sub-sections, the first sub-section was how to social influence the usage of social media over the undergraduate students, the second sub-section was to determine the perceived usefulness of social media, the third sub-section was to determine the perceived ease of use of social media, the fourth sub-section was to determine the behavioral intention to use of social media and the fifth sub-section was investigated the purpose of actual social media usage by undergraduate students. The section C has nine items in only one sub-section and eight items in four sub-sections using five-likert scale of strongly disagree (1), disagree (2), neither agree nor disagree (3), agree (4), and strongly agree (5). Section C of the questionnaire focused on the information behavior of undergraduate students on social media. The questionnaire was administered personally by the survey. The researcher at the point of administration gave enough time to the student to respond to the questionnaire without any interference. The researcher also ensured that the students responded to the administered questionnaire and the completely filled questionnaire was collected from the students. The administration of the data collection instrument took two weeks for its completion.

3.5 Method of Data Analysis

In this section, the theoretical background of the statistical techniques such as descriptive analysis, reliability analysis and confirmatory factor analysis are presented. Frequency and simple percentage were used to analyze the three objectives of the study. Collected data were coded and data presentation for research purposes using tables, Spearman Rank Order Correlation, the formula hypothesis and Structural Equation Modeling (SEM) analysis were used to determine the adoption of social media usage among students in Yangon University of Economics (Ywar Thar Gyi Campus).

3.5.1 Reliability Analysis

The study conducted a reliability test on undergraduate students of the Yangon University of Economics (Ywar Thar Gyi Campus), Cronbach alpha was used to determine the overall reliability of the questionnaire. Reliability is the scale construction counterpart of precision and accuracy in physical measurement. Reliability can be thought of as consistency in measurement. To establish the reliability of the data, the reliability coefficient (Cronbach Alpha) was verified. There are a number of different reliability coefficients. One of the most commonly used is Cronbach's alpha. Cronbach's alpha can be interpreted as a correlation coefficient; it ranges a value from 0 to 1. Robinson & Shaver (1973) suggested that if Alpha is greater than 0.7, it means high reliability and if Alpha is smaller than 0.3, it means low reliability. Before using the factor analysis, it is very important to test the reliability of the dimensions in the questionnaires. Cronbach's alpha, a statistical test used to examine the internal consistency of attributes, was determined for each dimension. This statistical test shows the attributes are related to each other and to the composite scores. The composite scores for each section of the questionnaires was obtained by summing up the scores of individual statements. Cronbach's alpha is defined as –

$$\alpha = \frac{K}{K-1}\left[1 - \frac{\sum_{i=1}^{k} s_i^{\,2}}{s_T^{\,2}}\right]$$

Where

α = Cronbach's alpha,

k = Number of Statement

$s_i^{\,2}$ = Variance of each statement

$s_T^{\,2}$ = Variance for sum of all items

If alpha value is high, then this suggests that all of the items are reliable and the entire test is internally consistent. If alpha is low, then at least one of the items is unreliable and must be identified via item analysis procedure. However, the Cronbach's alpha value should be above 0.7.

3.5.2 Testing for Sampling Adequacy

Kaiser-Meyer-Olkin (KMO) test is a measure of how suited the data is for factor analysis. The test measures sampling adequacy for each variable in the model and for the complete model. The statistics is a measure of the proportion of variance among variables that might be common variance. If lower the proportion, the more suited the data is to factor analysis. KMO takes the value between 0 and 1. A rule of thumb for interpreting the statistic. KMO value lies between 0.8 and 1.0 indicate the sampling is adequate. KMO value less than 0.6 indicates the sampling is not adequate and that remedial action should be taken. KMO values close to zero means that there are large partial correlations compared to the sum of correlations. In other words, there are widespread correlations which are a large problem for factor analysis.

The Bartlett's test of Spherically 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. For a large sample, Bartlett's test approximates a Chi-square distribution. However, the Bartlett's test compares the observed correlation matrix to the identity matrix. Therefore, the Bartlett's test forms something of a bottom-line test for large samples, but is less reliable for small samples. For factor analysis to be recommended suitable, the Bartlett's Test of Sphericity must be less than 0.05. In addition, very small values of significance (below 0.05) indicate a high probability that is significance relationship between the variables, whereas higher values (0.1 or above) indicate the data is inappropriate for factor analysis.

3.5.3 Confirmatory 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 approximate 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. 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 (Johnson, 2002) fifth edition.

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.

A fundamental equation of the common factor model is

$$y_j = \lambda_{j1}\eta_1 + \lambda_{j2}\eta_2 + \ldots + \lambda_{jm}\eta_m + \varepsilon_j \tag{3.1}$$

Where

y_j = the jth of p indicators (j=1, 2, …, p)

λ_{jm}= the factor loading relating variable j to the mth factor η

ε_j = the variance that is unique to indicator y_j

The model matrix terms,

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_p \end{bmatrix} = \begin{bmatrix} \lambda_{11} & \lambda_{12} & \cdots & \lambda_{1m} \\ \lambda_{21} & \lambda_{22} & \cdots & \lambda_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{p1} & \lambda_{p2} & \cdots & \lambda_{pm} \end{bmatrix} \begin{bmatrix} \eta_1 \\ \eta_2 \\ \vdots \\ \eta_p \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_p \end{bmatrix} \tag{3.2}$$

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

Assume that,

$E(\boldsymbol{\eta}) = \mathbf{0}_{(m\times 1)}$, $\quad V(\boldsymbol{\eta}) = \boldsymbol{\psi}_{(m\times m)}$

$E(\boldsymbol{\varepsilon}) = \mathbf{0}_{(p\times 1)}$ $\quad V(\varepsilon) = \boldsymbol{\Theta}_{(p\times p)}$

$E(\boldsymbol{\eta\eta}') = \boldsymbol{\psi}_{(p\times p)}$ $\quad E(\boldsymbol{\varepsilon\varepsilon}') = \boldsymbol{\Theta}_{(p\times p)}$ $\quad$ and $\quad$ Cov $(\boldsymbol{\varepsilon}, \boldsymbol{\eta}) = \mathbf{0}_{(p\times m)}$

The variance of y is

$$\begin{aligned} V(\mathbf{y}) = \mathbf{\Sigma} &= E(\mathbf{yy}') \\ &= E[(\Lambda\,\boldsymbol{\eta} + \boldsymbol{\varepsilon})\,(\Lambda\,\boldsymbol{\eta} + \boldsymbol{\varepsilon})'] \\ &= \Lambda\, E(\boldsymbol{\eta\eta}')\,\Lambda' + \Lambda\, E(\boldsymbol{\eta\varepsilon}')\,\Lambda' + E(\boldsymbol{\varepsilon\eta}')\,\Lambda' + E(\boldsymbol{\varepsilon\varepsilon}') \end{aligned}$$

so that

$$\mathbf{\Sigma} = \mathbf{\Lambda}\,\mathbf{\Psi}\,\mathbf{\Lambda}' + \mathbf{\Theta} \tag{3.3}$$

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

$$\mathbf{\Theta} = \begin{bmatrix} \Theta_1 & 0 & \cdots & 0 \\ 0 & \Theta_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \Theta_p \end{bmatrix}$$

Where $\mathbf{\Sigma}$ = the p × p symmetric covariance matrix of p indicators

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

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

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

Orthogonal factor

Johnson & Wichern (2002), the observable random vector **X**, with p components, has mean $\boldsymbol{\mu}$ and covariance matrix $\mathbf{\Sigma}$.

The factor model postulates that **X** is linearly dependent upon a few unobservable random variables F_1, F_2, …., F_m, called common factors, and p additional sources of variation e_1, e_2, … e_p, called errors or, sometimes, specific factors. in particular, the factor model can be selected as follows:

Factor is

$$\begin{aligned} X_1 - \mu_1 &= \ell_{11}F_1 + \ell_{12}F_2 + \ell_{13}F_3 + \ldots + \ell_{1m}F_m + \varepsilon_1 \\ X_2 - \mu_2 &= \ell_{21}F_1 + \ell_{22}F_2 + \ell_{23}F_3 + \ldots + \ell_{2m}F_m + \varepsilon_2 \\ \vdots & \qquad\qquad \vdots \\ X_p - \mu_p &= \ell_{p1}F_1 + \ell_{p2}F_2 + \ell_{p3}F_3 + \ldots + \ell_{pm}F_m + \varepsilon_p \end{aligned} \tag{3.4}$$

or in matrix notation,

$$\mathbf{X} - \boldsymbol{\mu}_{(p\times 1)} = \mathbf{L}\,\mathbf{F}_{(p\times m)\,(m\times 1)} + \boldsymbol{\varepsilon}_{(p\times 1)} \tag{3.5}$$

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 factors

The unobservable random vectors **F** and $\boldsymbol{\varepsilon}$ satisfy the following conditions:

F and $\boldsymbol{\varepsilon}$ are independent

$(\mathbf{F}) = \mathbf{0}$, Cov $(\mathbf{F}) = \mathbf{I}$

$(\boldsymbol{\varepsilon}) = 0$, Cov $(\boldsymbol{\varepsilon}) = \boldsymbol{\Psi}$, where $\boldsymbol{\Psi}$ is a diagonal matrix (3.6)

Covariance Structure

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

$$\boldsymbol{\Sigma} = \text{Cov}(\mathbf{X}) = \text{E}(\mathbf{X} - \boldsymbol{\mu})$$

$$= \mathbf{L}\text{E}(\mathbf{F}\mathbf{F}')\boldsymbol{L}' + \text{E s}(\boldsymbol{\varepsilon F}')\boldsymbol{L}' + \mathbf{L}\text{E}(\boldsymbol{F\varepsilon}') + \text{E}(\boldsymbol{\varepsilon\varepsilon}')$$

$$= \mathbf{L}\mathbf{L}' + \boldsymbol{\Psi}$$

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

$$\text{Cov}(\mathbf{X}) = \mathbf{L}\mathbf{L}' + \boldsymbol{\Psi} \tag{3.7}$$

Or

$$\text{Var}(X_i) = \ell_{i1}{}^2 + \cdots + \ell_{im}{}^2 + \psi_i$$

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

$$\text{Cov}(\mathbf{X}, \mathbf{F}) = \mathbf{L} \tag{3.8}$$

Or

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

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 factors is called the ith communality. That portion of Var $(X_i) = \sigma_{ii}$ due to the specific factor is called uniqueness or specific variance. Denoting the ith communality by $h_i{}^2$,

$$\frac{\sigma_{ii}}{Var(X_i)} = \frac{l_{i1}{}^2 + l_{i2}{}^2 + \cdots + l_{im}{}^2}{communality} + \frac{\psi_i}{Specific\ Variance}$$

or

$$\text{h}_\text{i}{}^2 = \ell_{i1}{}^2 + \ell_{i2}{}^2 + \cdots + \ell_{im}{}^2 \tag{3.9}$$

and

$$\sigma_{ii} = h_i{}^2 + \psi, \quad \text{i} = 1, 2, \cdots, \text{p}$$

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

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 factors analysis is to determine a few important common factors.

If $\mathbf{\Sigma}$ appears to deviate significantly from a diagonal matrix, then a factor model can be entertained, and the initial problem is one of estimating the factor loadings $\boldsymbol{\ell}_{ij}$ and specific variances $\boldsymbol{\psi}_i$. Two most popular methods of the parameter estimation are the principal component method and the maximum likelihood method. the solution from either method can be rotated in order to simplify the interpretation of factors. If the factor model is appropriate for the problem to try more than one method of solutions should be consistent with one another (Wichern, 2002).

The Principal Component Method (Principal Factor)

Mertler & Vannatta (2016), the spectral decomposition provides us with one factoring of the covariance matrix $\mathbf{\Sigma}$. Let $\mathbf{\Sigma}$ have eigenvalue – eigenvector pairs (λ_i,$_i$) with $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0$. then,

$$\mathbf{\Sigma} = \lambda_1 \boldsymbol{e}_1 \boldsymbol{e}_1' + \lambda_2 \boldsymbol{e}_2 \boldsymbol{e}_2' + \cdots + \lambda_p \boldsymbol{e}_p \boldsymbol{e}_p' \tag{3.10}$$

$$= [\sqrt{\lambda_1}\mathbf{e}_1 \vdots \sqrt{\lambda_1}\mathbf{e}_2 \vdots \cdots \vdots \sqrt{\lambda_p}\mathbf{e}_p] \begin{bmatrix} \sqrt{\lambda_1}\mathbf{e}_1' \\ --- \\ \sqrt{\lambda_2}\mathbf{e}_2' \\ --- \\ \vdots \\ --- \\ \sqrt{\lambda_p}\mathbf{e}_p' \end{bmatrix}$$

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

$$\mathbf{\Sigma}_{(p\times p)} = \mathbf{L}_{(p\times p)}\mathbf{L}'_{(p\times p)} + \mathbf{0}_{(p\times p)} \quad = \mathbf{LL}' \tag{3.11}$$

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

Although the factor analysis representation of $\mathbf{\Sigma}$ is exact, it is not particularly useful. It employs as many common factors as there are variables and does not allow for any variation in the specific factors $\boldsymbol{\varepsilon}$. One approach when the last p-m eigenvalues are small, is to neglect the contribution of $\lambda_m e_m e_{m+1}' + \cdots + \lambda_p e_p e_p'$ to $\mathbf{\Sigma}$. Neglecting this contribution, the approximation is obtained.

$$\boldsymbol{\Sigma} = [\sqrt{\lambda_1}\mathbf{e}_1 \vdots \sqrt{\lambda_1}\mathbf{e}_2 \vdots \cdots \vdots \sqrt{\lambda_p}\mathbf{e}_p] \begin{bmatrix} \sqrt{\lambda_1}\mathbf{e}_1' \\ --- \\ \sqrt{\lambda_2}\mathbf{e}_2' \\ --- \\ \vdots \\ --- \\ \sqrt{\lambda_p}\mathbf{e}_p' \end{bmatrix}$$

$$\boldsymbol{\Sigma}_{(\mathbf{p}\times\mathbf{p})} = \mathbf{L}_{(\mathbf{p}\times\mathbf{p})}\mathbf{L}'_{(\mathbf{p}\times\mathbf{p})} \tag{3.12}$$

The approximate representation is assuming that the specific factors $\boldsymbol{\varepsilon}$ are of minor importance and can also be ignored in the factoring of $\boldsymbol{\Sigma}$.

The approximation can be written as following

$$\boldsymbol{\Sigma} = \mathbf{L}\,\mathbf{L}' + \boldsymbol{\Psi} \tag{3.13}$$

$$\boldsymbol{\Sigma} = [\sqrt{\lambda_1}\mathbf{e}_1 \vdots \sqrt{\lambda_1}\mathbf{e}_2 \vdots \cdots \vdots \sqrt{\lambda_p}\mathbf{e}_p] \begin{bmatrix} \sqrt{\lambda_1}\mathbf{e}_1' \\ --- \\ \sqrt{\lambda_2}\mathbf{e}_2' \\ --- \\ \vdots \\ --- \\ \sqrt{\lambda_p}\mathbf{e}_p' \end{bmatrix} + \begin{bmatrix} \tilde{\psi}_1 & 0 & \cdots & 0 \\ 0 & \tilde{\psi}_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \tilde{\psi}_p \end{bmatrix}$$

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

To apply this approach to a data set $x_1, x_2, \ldots, x_n$, it is customary first to center the observations by subtracting the sample mean $\bar{x}$. The cantered observations

$$\mathbf{x}_j - \bar{\boldsymbol{x}} = \begin{bmatrix} \mathbf{x_{j1}} \\ \mathbf{x_{j2}} \\ \vdots \\ \mathbf{x_{jp}} \end{bmatrix} = \begin{bmatrix} \bar{\mathbf{x}}_1 \\ \bar{\mathbf{x}}_2 \\ \vdots \\ \bar{\mathbf{x}}_p \end{bmatrix} = \begin{bmatrix} \mathbf{x_{j1}} & - & \bar{\mathbf{x}}_1 \\ \mathbf{x_{j2}} & - & \bar{\mathbf{x}}_2 \\ \vdots & \vdots & \vdots \\ \mathbf{x_{jp}} & - & \bar{\mathbf{x}}_p \end{bmatrix} \quad , j = 1, 2, \ldots, n \tag{3.14}$$

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 desirable to work with the standardized variables.

$$\mathbf{Z}_j = \begin{bmatrix} \frac{(x_{1j} - \bar{x}_1)}{\sqrt{s_{11}}} \\ \frac{(x_{2j} - \bar{x}_2)}{\sqrt{s_{22}}} \\ \vdots \\ \frac{(x_{pj} - \bar{x}_p)}{\sqrt{s_{pp}}} \end{bmatrix}, \qquad j = 1,2, \ldots, n \tag{3.15}$$

This sample covariance matrix is the sample correlation matrix **R** of the observations $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n$, standardization avoids the problems of having one variable with large variance unduly influencing the determination of factor loadings. The sample covariance matrix **S** or the sample correlation matrix **R** is known as principal component solution.

Principal Component Solution

The principal component factor analysis of the sample covariance matrix S is 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 $\hat{\lambda}_1 \geq \hat{\lambda}_2 \geq \hat{\lambda}_3 \geq \cdots \geq \hat{\lambda}_p$.

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

$$\tilde{\mathbf{L}} = \left[\sqrt{\hat{\lambda}_1, \hat{e}_1} \mid \sqrt{\hat{\lambda}_2, \hat{e}_2} \mid \sqrt{\hat{\lambda}_3, \hat{e}_3} \mid \ldots \mid \sqrt{\hat{\lambda}_p, \hat{e}_p} \right] \tag{3.16}$$

The estimated specific variance was provided by the diagonal elements of the matrix S - $\tilde{L}\tilde{L}'$.

$$\tilde{\Psi} = \begin{bmatrix} \tilde{\psi}_1 & 0 & \cdots & 0 \\ 0 & \tilde{\psi}_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \tilde{\psi}_p \end{bmatrix} \text{ with } \tilde{\psi}_i = s_{ij} - \sum_{j=1}^{m} \tilde{\ell}_{ij}^2 \tag{3.17}$$

Communalities are estimated as

$$\widetilde{h_i}^2 = \tilde{\ell}_{i1}^2 + \tilde{\ell}_{i2}^2 + \cdots + \tilde{\ell}_{im}^2 \tag{3.18}$$

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

Residual Matrix

If the number of common factors is not determined by a priori considerations based on the estimated eigenvalues in much the same manner as with principal component, consider the residual matrix

$$\mathbf{S} - (\tilde{\mathbf{L}}\,\tilde{\mathbf{L}}\,' + \tilde{\mathbf{\Psi}}) \qquad (3.19)$$

resulting from the approximation of S by the principal component solution. The diagonal elements are zero. Sum of squared entries of

$$(\mathbf{S} - (\tilde{\mathbf{L}}\,\tilde{\mathbf{L}}\,' + \tilde{\mathbf{\Psi}})) \leq \hat{\lambda}^2{}_{m-1} + \cdots + \hat{\lambda}^2{}_{p} \qquad (3.20)$$

The contributions of the first few factors to the sample variances of the variables should be large. 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, $s_{11} + s_{22} + \cdots + s_{pp} = \mathrm{tr}\,(\mathbf{S})$, from the first common factor is then

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

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

$$\begin{pmatrix} Proportion\ of\ total \\ sample\ variance \\ due\ to\ jth\ factor \end{pmatrix} = \begin{cases} \dfrac{\hat{\lambda}_j}{s_{11} + s_{22} + \ldots + s_{pp}} & for\ a\ factor\ analysis\ of\ S \\ \dfrac{\hat{\lambda}_j}{p} & for\ a\ factor\ analysis\ of\ R \end{cases} \qquad (3.21)$$

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 (Johnson, 2002).

Factor Rotation

All factor loadings obtained from the initial loadings by an orthogonal transformation have the same ability to reproduce the covariance matrix. An orthogonal transformation of the factor loadings as well as the implied orthogonal transformation of the factors is called factor rotation.

If $\hat{\mathbf{L}}$ if the p x m matrix of estimated factor loadings obtained by any method; then

$\hat{\mathbf{L}}^* = \hat{\mathbf{L}}\ \mathbf{T}$, where $\mathbf{TT}\,' = \mathbf{T}\,'\mathbf{T} = \mathbf{I}$ is a p × m matrix of rotated loadings. (3.22)

The estimated covariance matrix remains unchanged, since

$$\mathbf{L}\,\mathbf{L}\,' + \mathbf{\Psi} = \mathbf{LTT'L} + \mathbf{\Psi} = \mathbf{L^*}\,\mathbf{L^*}\,' + \mathbf{\Psi} \qquad (3.23)$$

Equation indicates that the residual matrix, $\boldsymbol{Sn} - \mathbf{LL'} - \boldsymbol{\Psi} = \mathrm{S}_n - \mathbf{L}^* \mathbf{L}^{*\prime} + \boldsymbol{\Psi}$ remains unchanged. The specific variance $\widehat{\psi}_i$ and hence the communalities $\widehat{\psi}_i^2$, are unaltered. Thus, from a mathematical viewpoint, it is immaterial whether $\hat{L}$ or $\hat{L}*$ is obtained.

The original loading may not be readily interpretable. It is usual practice to rotate 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 possible to get this simple structure and the rotated loading for the decathlon data provide a clear pattern. Graphical and analytical methods should be concentrated for determining an orthogonal rotation to a simple structure (Wichern, 2002).

The Varimax Rotation

When principal components analysis and factor analysis identify underlying factors. They do this using a greedy algorithm. They begin by identifying the first component in a way that best explains the variance, and continue by identifying the next.

In statistics, in such a way that the component explains the largest possible amount of residual variance. A varimax rotation is used to simplify the description of a certain subspace. The actual coordinate system is unchanged, it is a perpendicular base that rotates to align with those coordinates. The subspace found by principal component analysis or statistical analysis is described as a dense basis with many non-zero weights, which makes interpretation difficult. Varimax is so called because it maximizes the sum of the variance of squared loadings (squared correlations between variables and factors). In addition, the varimax rotation that places the factor axes at right angles to each other is most often chosen. Typically, rotation reduces the number of confounding variables and improves interpretation. Almost all applications of principal component analysis and factor analysis in survey research use the method of varimax rotation (Johnson, 2002).

Oblique Rotation

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. Proms rotation method is computationally faster than obtimin nation and used for the large datasets.

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, …, n. That is, factor scores

$\mathbf{F_j}$ = estimated of the values $\mathbf{f_j}$, attained by $\mathbf{F_j}$, for j = 1, 2, …, n.

The estimation situation is complicated by the factor that the unobserved quantities $\mathbf{f_j}$ and $\boldsymbol{\varepsilon}_\mathbf{j}$ outnumber the observation $\mathbf{x_j}$.

Starting again with the original factor model $\mathbf{X}-\boldsymbol{\mu} = \mathbf{LF} + \boldsymbol{\varepsilon}$, 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 $\mathbf{X} - \boldsymbol{\mu} = \mathbf{LF} + \boldsymbol{\varepsilon}$ has an $\mathbf{N_p}$ $\mathbf{(0, LL' + \Psi)}$ distribution. Moreover, the joint distribution of $\mathbf{(X - \boldsymbol{\mu})}$ and $\mathbf{F}$ is $\mathbf{N_{m+p}}$ $\mathbf{(0, \Sigma^*)}$, where

$$\boldsymbol{\Sigma}^* = \begin{bmatrix} \mathbf{LL' + \Psi} & \mathbf{L} \\ \mathbf{L'} & \mathbf{I} \end{bmatrix} \tag{3.24}$$

and $\mathbf{0}$ is an (m + p) × 1 vector of zeros. The conditional distribution of $\mathbf{F|x}$ is multivariate normal with mean

$$\mathbf{E(F|x) = L' \Sigma^{-1}(X - \boldsymbol{\mu}) = L' (LL' + \Psi)^{-1}(X - \boldsymbol{\mu})} \tag{3.25}$$

and covariance

$$\mathrm{Cov}\ \mathbf{(F|x) = I - L' \Sigma^{-1} L = I - L' (LL' + \Psi)^{-1} L} \tag{3.26}$$

The quantities $\mathbf{L' (LL' + \Psi)^{-1}}$ 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

$$\hat{\mathbf{f}}_j = \hat{\mathbf{L}}\hat{\Sigma}^{-1}(\mathbf{x}_j - \bar{\mathbf{x}}) = \hat{\mathbf{L}}'(\hat{\mathbf{L}}\hat{\mathbf{L}}' + \boldsymbol{\Psi})^{-1}(\mathbf{x}_j - \bar{\mathbf{x}}) \quad j = 1, 2, \ldots, n \tag{3.27}$$

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

$$\hat{\mathbf{L}}'(\hat{\mathbf{L}}\hat{\mathbf{L}}' + \boldsymbol{\Psi})^{-1} = (\mathbf{I} + \hat{\mathbf{L}}'\boldsymbol{\Psi}^{-1}\hat{\mathbf{L}})^{-1}\hat{\mathbf{L}}'\boldsymbol{\Psi}^{-1} \tag{3.28}$$

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

If a correlation matrix is factored,

$$\hat{\mathbf{F}}_j = \hat{\mathbf{L}}'_2\,\hat{\mathbf{p}}^{-1}\boldsymbol{Z_j}, \qquad j = 1, 2, \ldots, n \tag{3.29}$$

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

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

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

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

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 (Johnson, 2002).

3.5.3.1 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 E) that resembles the sample variance-covariance matrix (symbolized as S) as closely as possible. For instance, in overidentified models, perfect fit is rarely achieved (ie., ES). 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:

$$F_{ML} = \ln|\mathbf{S}| - \ln|\mathbf{\Sigma}| + \text{trace}[(\mathbf{S})(\mathbf{\Sigma}^{-1})] - p \tag{3.30}$$

where $|\mathbf{S}|$ is the determinant of the input variance-covariance matrix. $|\mathbf{\Sigma}|$ 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 in 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 (Wichern, 2002).

3.5.3.2 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:

$$\chi^2 = F_{ML}(N-1) \tag{3.31}$$

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

The model χ^2 exceeds the critical value, and thus the null hypothesis that $S = \Sigma$ is rejected. Thus, a statistically significant χ^2 (latent variable software provides the exact probability value of the model χ^2) 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.

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,

$$b = \frac{p(p+1)}{2} \tag{3.32}$$

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).

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 x distribution includes a non-centrality parameter (NCP), which expresses the degree of model misspecification. The NCP is estimated as χ^2-df (if the result is a negative number, NCP = 0). When the fit of a model is perfect, NCP = 0 and a central x distribution hold. 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. x). To foster the conceptual basis of the calculation of RMSEA, the NCP is rescaled to the quantity d: = χ^2- $\frac{df}{(N-1)}$.The RMSEA is then computed:

$$\text{RMSEA} = \text{SQRT}\left[\frac{d}{df}\right] \tag{3.33}$$

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 0.08.

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:

$$\text{CFI} = \frac{1-max-[(\chi^2_T - df_T),0]}{max(\chi^2_T - df_T),(\chi^2_B - df_B),0]} \tag{3.34}$$

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 non-centrality parameter, meaning that it uses information from expected values of χ_T^2 or χ_B^2 the noncentral χ^2 distribution associated with S ≠ Σ.

3.5.3.3 Average Variance Extracted (AVE)

In statistics (classical test theory), average variance extracted (AVE) is a measure of the amount of variance that is captured by a construct in relation to the amount of variance due to measurement error (Ab Hamid, 2017).

The average variance extracted can be calculated as follows:

$$\text{AVE} = \frac{\sum_{i=1}^{k} \lambda_i^2}{\sum_{i=1}^{k} \lambda_i^2 + \sum_{i=1}^{k} Var(e_i)} \tag{3.35}$$

where, k = the number of items,

λ_i = the factor loading of item i

$\mathrm{Var}(e_i)$ = the variance of the error of item i

3.5.3.4 Composite Reliability (CR)

Composite reliability (sometimes called construct reliability) is a measure of internal consistency in scale items, much like Cronbach's alpha (Netemeyer, 2003).

It can be thought of as being equal to the total amount of true score variance relative to the total scale score variance (Brunner & Süß, 2005). Alternatively, it's an "indicator of the shared variance among the observed variables used as an indicator of a latent construct" (Fornell & Larcker, 1981).

Confirmatory Factor Analysis is one way to measure composite reliability, and it is widely available in many different statistical software packages. By hand, the calculations are a little cumbersome. The formula is;

$$\text{CR} = \frac{(\sum_{i=1}^{k} \lambda_i)^2}{(\sum_{i=1}^{k} \lambda_i)^2 + \sum_{i=1}^{k} Var(e_i)} \tag{3.36}$$

where: λ_i = completely standardized loading for the ith indicator

$\mathrm{Var}(e_i)$ = variance of the error term for the ith indicator

k = number of indicators

CHAPTER IV
RESULTS AND FINDINGS

This chapter presents the analysis the adoption of social media usage among students in Yangon University of Economics (Ywar Thar Gyi Campus) based on the results of data collected from 350 students. The statistical analysis used in this study include demographic data analysis, measurement model analysis, convergent validity, discriminant validity, reliability test, confirmatory factor analysis, the structural equation modeling (SEM) analysis.

4.1 Characteristics of Respondents

The demographic characteristics of the respondents are shown in Table 4.1. According to age of the respondents the highest number of the respondents i.e. 97 (27.7%) are age of 19 years, followed by 18 years with 80 (22.9%), 20 years with 64 (18.3%), 21 years with 38 (10.9%), 23 years with 31 (8.9%), 22 years with 29 (8.3%) and 17 years with 10 (2.9%) while the least are respondents of 24 years with 1 (0.3%). Mean value of age is 19.73 and standard deviation is 0.087.

In classification of the number of the respondents, indicates that 275 (78.6%) of the respondents are female while 75 (21.4%) are male. Thus, majority of the respondents are female.

Current Residence of the Respondents indicates that 199 (56.9%) of the respondents are in hostel (Yes) while 151 (43.1%) are not in hostel (No). Hence, majority of the respondents are in hostel.

Religion of the respondents reveals that highest number 336 (96.0%) of the respondents are in Buddhism, this is followed by the Christian religion students' constituting 2.3% and Islam religion students indicated that 1.4% respectively. The least percentage (0.3%) of the respondents are in others religion. This implies that Buddhism religion students constituted the highest number of the respondents.

Major Specialization of the respondents reveals that majority of the respondents are B.Com (25.1%), B.Econ(Stats) (18.3%), BPA (16.3%), BBA (13.1%), B.Dev.S (11.7%), B.Econ (Eco) (6.6%), and B.Act (5.7%) major students respectively. The least percentage (3.1%) of the respondents are in BPS major students. Hence, majority of the respondents are B.Com major students.

Years of attendance of the respondents indicates that the highest number of the respondents (46.6%) are in first year students, followed by final year/ H_2 and H_3/ qualified students (17.1%), the second year (first semester) students constituting (14.3%) and third year/ H_1 students (14.0%) respectively. The least percentage (8.0%) of the respondents are in second year (second semester) students. Therefore, majority of the respondents are first year students.

Use of social media more of the respondents reveals that the respondents use Facebook (36.0%), Twitter and Instagram (23.1%) respectively. Linked In (12.6%), and Tik Tok (5.1%) indicated respectively. This implies that Facebook applications are the most used social media tools among undergraduate.

Use social media in a day of the respondents shows hourly basis in which the respondents utilize social media, the table shows that highest number 145 (41.4%) of the respondents uses social media between 1-3 hours daily, followed by 111 (31.7%) of the respondents who usually spend between 3-5 hours when using social media. However, only 19 (5.4%) of the respondents usually spend seven hours or more when using social media.

Table 4.1 Characteristics of Respondents

Variable	Frequency	Percentage (%)
Age		
17 (years)	10	2.9
18	80	22.9
19	97	27.7
20	64	18.3
21	38	10.9
22	29	8.3
23	31	8.9
24	1	0.3
Gender		
Male	75	21.4
Female	275	78.6
In Hostel		
Yes	199	56.9
No	151	43.1

Table 4.1 Characteristics of Respondents (continued)

Variable	Frequency	Percentage (%)
Religion		
Buddhism	336	96.0
Christian	8	2.3
Islam	5	1.4
Others	1	0.3
Major Specialization		
B.Com	88	25.1
B.Act	20	5.7
BBA	46	13.1
B.Econ(Stats)	64	18.3
BPS	11	3.1
B.Econ(Eco)	23	6.6
B.Dev.S	41	11.7
BPA	57	16.3
Years of Attendance		
First year	129	46.6
Second year (First semester)	54	14.3
Second year (Second semester)	49	8.0
Third year/H_1	52	14.0
Final year/H_2 and H_3/ Qualified	66	17.1
Use of social media more		
Facebook	126	36.0
Twitter	81	23.1
Instagram	81	23.1
Linked In	44	12.6
TikTok	18	5.1
Use social media in a day		
Less than 1 hour	22	6.3
1-3 hours	145	41.4
3-5 hours	111	31.7
5-7 hours	53	15.1
Seven hours or more	19	5.4

Source: Survey Data (2023)

4.2 The Reliability Analysis of the Factors

Firstly, the items of usages and the effects social media on students were conducted with reliability analysis. The reliability and the internal consistency of the item's 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 five factors ranged from 0.811 to 0.903 for the five factors such as are social influence, perceived usefulness, perceived ease of use, behavioral intention to use social medias, actual usage of social medias. 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 0.942 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 social influence was 0.811 and that for perceived usefulness, perceived ease of use, behavioral intention to use social medias and are 0.842, 0.857 and 0.925 respectively. The last factor of the actual usage of social medias is .903 which is more than the minimum value for accepting value.

Table 4.2 Reliability Analysis Results

No.	Factor	Cronbach's Alpha	No of items
1	Social Influence	0.811	8
2	Perceived Usefulness	0.842	8
3	Perceived Ease of Use	0.857	8
4	Behavioral Intention to Use Social Media	0.925	9
5	Actual Usage of Social Media	0.903	8
Total	All items	0.942	41

Source: Survey Data (2023)

4.3 Factors Influencing of Social Media Among Students

In this section, social influence, perceived usefulness, perceived ease of use, behavioral intention to use social media and actual usage of social media are examined by descriptive statistics.

The mean value of social media factors is given in Table 4.3.

Table 4.3 Mean Value of the Factors

Factors	Mean	Std. Deviation
Social Influence	3.64	0.60
Perceived Usefulness	3.71	0.56
Perceived Ease of use	3.87	0.57
Behaviour Intention to use Social Network	3.90	0.58
Actual Usage of Social Network	3.95	0.59
Overall Mean	3.81	0.44

Source: Survey Data (2023)

According to Table 4.3, the overall mean value of student's perception towards factors influencing of social media among students is 3.81, thus indicating the agree level of perception by students. A maximum mean value of 3.95 indicates that the actual usage of social network. The perception on social influence has minimum mean 3.64 and it means the social influence of students has a relatively weaker impact on students' social media usage. Overall, these findings indicate that students view social media as both useful and easy to use. They also express a strong intention to continue using these platforms. This suggests that social media has become an integral part of their lives, with fairly consistent opinions across the surveyed population. The slightly higher mean values hint at active usage, while the standard deviations show a moderate level of variation in usage patterns.

4.4 Confirmatory Factor Analysis for the Factors of Social Media Usage

Denoted that factors of social media impact on students conducted by confirmatory factor analysis with structural equation modeling. Confirmatory factor analysis is used to test the relationship between the observed variable and the underlying factors of social media use and the effects of social media. Structural equation modeling (SEM) includes two dimensions model and structural model. First, the skewness and kurtosis values of each factor and their standardized residual variance matrix were checked for multivariate normality. For each variable, Skewness and kurtosis values are between -2 and +2. By examining the standardized residual covariance matrix; Residual values are less than 0.05, which are signs of normality. Therefore, all variables satisfy a multivariate normal distribution.

Factor Analysis

The principal factor method was used to generate the initial solution. The total variance explained at five factors (social influence, perceived usefulness, perceived ease of use, behavioral intention to use social medias, behavior adoption to use social media) are 57.40% of the overall variance and their eigenvalues are greater than 1. Items of each factor are greater than 0.5. From the varimax-rotated factor matrix, five factors with 41 variables are defined by the original variables.

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 0.940 which is meritorious. 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 (4.4).

Table 4.4 Kaiser-Meyer-Olkin KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	0.94
Bartlett's Test of Sphericity Approx. Chi-Square	8662.04
Degree of freedom(df)	820
p-value	0.00

Source: Survey Data (2023)

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 five point are small and the distances between then are very close and similar in the eigenvalue graph.

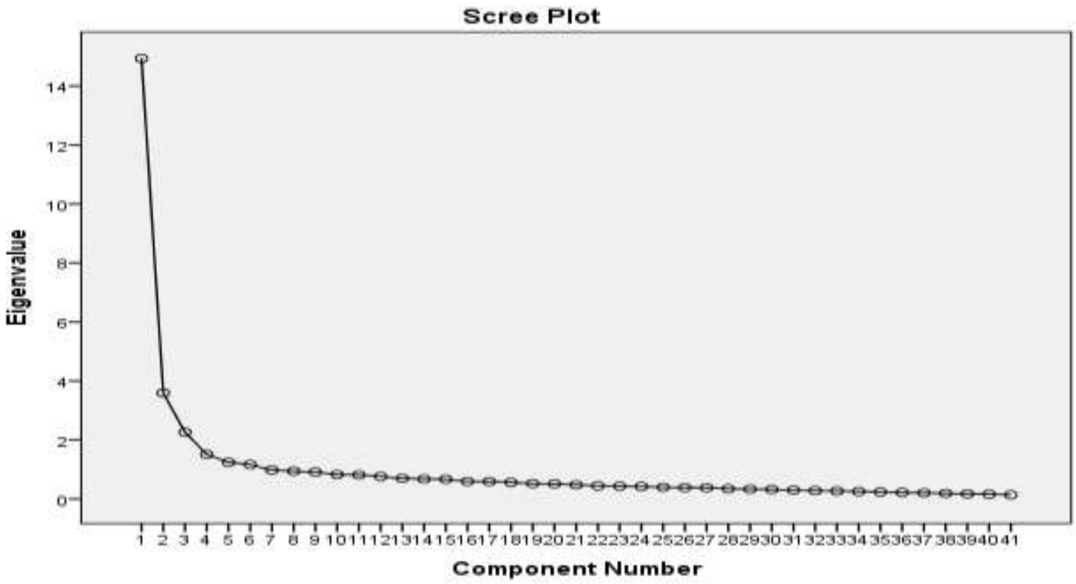

Figure (4.1) The Scree Plot for initial Variables

Source: Survey Data (2023)

4.5 Structural Equation Modeling for the Factors of Social Media Usage

Structural equation modeling (SEM) which examines a set of relationships between one or more observed independent variables, either continuous or discrete and one or more dependent variables, either continuous or discrete: both of which can either be factor or measured variables by combining factor analysis and path analysis (Kapaln, 2000) was applied in this study.

In this study, the factors of social media usage by students was conducted by structural equation modelling (SEM) and confirmatory factor analysis (CFA) tools for data analysis and testing the relationship between variables. Structural equation modeling is a family of multivariate statistical analysis methods used to model a network of complex structural relationships between one or more measured variables and latent constructs. Confirmatory factor analysis (CFA) method is used to verify the factor structure of a set of observed variables (Torsten, & Christian, 2012). The proposed equation model that explain educational usage of social media was constructed using five latent variables, namely, social influence, perceived usefulness, perceived ease of use, behavioral intention to use social medias and actual usage of social media were examined. This study got five factors in the total variance experienced precisely the number of factors targeted. Furthermore, the model accounted for 57% of the total variance, a reasonable and meaningful percentage in the context. The results are presented in Table 4.5.

Table 4.5 Total Variance Explained

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	14.936	36.429	36.429	14.936	36.429	36.429	11.703	28.543	28.543
2	3.592	8.760	45.188	3.592	8.760	45.188	3.572	8.713	37.256
3	2.260	5.513	50.701	2.260	5.513	50.701	3.212	7.834	45.090
4	1.509	3.682	54.383	1.509	3.682	54.383	3.072	7.493	52.583
5	1.239	3.022	57.405	1.239	3.022	57.405	1.977	4.822	57.405
6	1.160	2.829	60.235						
7	.975	2.379	62.614						
8	.939	2.291	64.905						
9	.908	2.214	67.119						
10	.823	2.008	69.127						
11	.813	1.982	71.110						
12	.759	1.851	72.961						
13	.695	1.695	74.655						
14	.673	1.641	76.296						
15	.664	1.620	77.917						
16	.590	1.438	79.355						
17	.588	1.433	80.788						
18	.558	1.360	82.148						
19	.519	1.267	83.414						
20	.511	1.247	84.662						
21	.474	1.155	85.817						
22	.441	1.077	86.894						
23	.432	1.053	87.946						
24	.420	1.025	88.971						
25	.394	.961	89.931						
26	.381	.929	90.860						
27	.376	.916	91.776						
28	.341	.832	92.609						
29	.329	.803	93.411						
30	.320	.780	94.192						
31	.296	.723	94.915						
32	.276	.673	95.588						
33	.266	.648	96.236						
34	.249	.608	96.844						
35	.232	.565	97.409						
36	.217	.530	97.939						
37	.203	.495	98.434						
38	.186	.454	98.888						
39	.168	.409	99.297						
40	.154	.375	99.672						
41	.135	.328	100.000						

Source; Survey Data (2023)

4.5.1 Measurement Model of Confirmatory Factor Analysis (CFA)

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 4.6. 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 social influence accounts from 0.597 to 0.830. Factor loads for perceived usefulness accounts from 0.472 to 0.737. Factor loads of perceived ease of use accounts from 0.522 to 0.717. Factor loads for behavioral intention to use social medias from 0.615 to 0.794. Factor loads for behavior adoption of social media (or) actual usage of social medias accounts from 0.534 to 0.805.

The Composite Reliability (CR) measure is a useful method of measuring reliability by presenting a precise value through numerical loadings in a constructed formula. The term Average Variance Extracted (AVE) is defined as the amount of average variance contained in an independent variable that describes the latent construct. When discriminant validity is greater than one factor, AVE can be used to assess the convergence of each factor. Table 4.10 shows that the result of the requirement for convergent validity and reliability of the questionnaire.

4.5.1.1 Convergent Validity

The comparative amount of convergent validity is determined by the implementation of indicators that include factor loadings, variance extracted and reliability that consists of Cronbach's Alpha and composite reliability. According to (Hair et al., 1998), when all constructs' reliability coefficient and composite reliability (CR) exceeds 0.7, then it shows the internal consistency between numerous measurements of a construct. This is apparent in Table 4.6 where Cronbach's alpha scores are higher than 0.7 and constructs' composite reliabilities range from 0.813 to 0.906. Moreover, all Average Variance Extracted (AVE) values that are between 0.357 and 0.518 are fulfilling the standard of describing's at least half of variance extracted from a group of items (Falk & Miller, 1992) that are fundamentals of the latent construct. Hence, the range used to assess the constructs is believed to attain convergent validity.

Table 4.6 Convergent Validity Results for Each Factor

Constructs	Items	Factor Loading	Cronbach's Alpha	Composite Reliability CR	Average Variance Extracted AVE
Social Influence	SI-1	0.683	0.811	0.888	0.501
	SI-2	0.726			
	SI-3	0.651			
	SI-4	0.796			
	SI-5	0.647			
	SI-6	0.830			
	SI-7	0.597			
	SI-8	0.701			
Perceived Usefulness	PU-1	0.668	0.842	0.813	0.357
	PU-2	0.586			
	PU-3	0.695			
	PU-4	0.737			
	PU-5	0.487			
	PU-6	0.472			
	PU-7	0.562			
	PU-8	0.517			
Perceived Ease of use	PE-1	0.630	0.857	0.817	0.360
	PE-2	0.614			
	PE-3	0.554			
	PE-4	0.589			
	PE-5	0.553			
	PE-6	0.717			
	PE-7	0.600			
	PE-8	0.522			
Behavioral Intention to Use Social medias	BI-1	0.711	0.925	0.906	0.518
	BI-2	0.765			
	BI-3	0.615			
	BI-4	0.765			
	BI-5	0.671			
	BI-6	0.760			
	BI-7	0.794			
	BI-8	0.752			
	BI-9	0.620			
Actual Usage of Social media	BA-1	0.747	0.903	0.894	0.516
	BA-2	0.618			
	BA-3	0.725			
	BA-4	0.534			
	BA-5	0.780			
	BA-6	0.805			
	BA-7	0.739			
	BA-8	0.756			

Source: Survey Data (2023)

4.5.1.2 Discriminant Validity

As shown in Table 4.7, all AVE values are greater than the squared correlation between the constructs in the measurement model (Hair et al., 1998). Therefore, all conditions for the discriminant validity are fulfilled. With an AVE value greater than 0.5, the construct should be at least 50% of the measurement variance. Discriminant value was determined by Partial Least Squares (Smart PLS ver. 3.2.6).The loadings and cross-loadings are shown in Table 4.6, and a thorough examination of loadings and cross-loadings show that all the measurement items are broadly loaded on their own latent constructs, rather than loading on other constructs. AVE analysis is present in Table 4.6. The AVE scores' square root is represented by the bold diagonal elements in Table 4.7. On the contrary, the correlation between constructs is indicated by off-loading diagonal elements. The table clearly shows that the AVE values' square root is present between the ranges of 0.600 and 0.902, which is greater than the standard value of 0.5. In contrast to all other correlations for every construct, the AVE is apparently greater, which shows that there is a larger variance of all constructs with their own measures, as compared to model's other constructs that highlight the discriminate validity.

Table 4.7 Fornell-Larcker Scale

	SI	PUL	PEU	BIN	AUS
SI	**0.708**				
PUL	0.206	**0.902**			
PEU	0.227	0.568	**0.600**		
BIN	0.135	0.581	0.784	**0.720**	
AUS	0.142	0.530	0.772	0.848	**0.718**

Source: Survey Data (2023)

4.5.1.3 Goodness of Fit Indices for the Measurement Model

In CFA, several statistical tests are used to determine how well the model fits to the data. A good fit between the model and the data does not mean that the model is correct, or even that it explains a large proportion of the covariance. A good model fit only indicates that the model is plausible. When reporting the results of a confirmatory factor analysis, one is urged to report: the proposed models, any modifications made, which measures identify each latent variable, correlations between latent variables. With regard to selecting model fit statistics to report, one should not simply report the statistics that estimate the best fit, though this may be temping. Through several varying opinions exists, Kline (2010) recommends reporting the chi-squared test, the root mean square error of approximation (RMSEA), the comparative fit index (CFI), and the standardized root mean square residual (SRMR). In this study, absolute fit indices include the chi-squared test, RMSEA, AGFI, CFI and SRMR. The results of this value are showed in Table 4.8.

Table 4.8 Goodness of Fit Criteria for the Measurement Model

Goodness of Fit Index	Model Results
Chi-Square/df	2.56
RMSEA	0.06
GFI	0.91
AGFI	0.89
CFI	0.90
SRMR	0.08

Source: Survey Data (2023)

The root mean square error of approximation (RMSEA) avoids issues of sample size by analyzing the discrepancy between the hypothesized model, with optimally chosen parameter estimates, and the population covariance matrix. The RMSEA range from 0 to 1, with smaller values indicating better model fit. A value of 0.08 or less is indicative of acceptable model fit.

The goodness of fit index (GFI) is a measure of fit between the hypothesized model and the observed covariance matrix. The adjusted goodness of fit index (AGFI) corrects the GFI, which is affected by the number of indicators of each latent variable. The GFI and AGFI range between 0 and 1, with a value of over 0.9 generally indicating acceptable model fit.

The comparative fit index (CFI) analyzes the model fit by examining the discrepancy between the data and the hypothesized model, while adjusting for the issues of sample size inherent in the chi-squared test of model fit and normed fit index. CFI values range from 0 to 1, with larger values indicating better fit. A CFI value of 0.90 or larger was considered to indicate acceptable model fit (Bentler, 1999).

The standardized root mean square residual (SRMR) are the square root of discrepancy between the sample covariance matrix and the model covariance matrix. The SRMR ranges from 0 to 1, with a value 0.08 or less being indicative of an acceptable model.

According to the Table 4.8, the results of chi-squared test, RMSEA, GFI, AGFI, CFI and SRMR are indicative of an acceptable model fit. Therefore, it can be said that the measurement model provided a good fit to the data.

4.5.2 Structural Model Validity for the Adoption 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 adoption of social media and is shown in Figure 4.2.

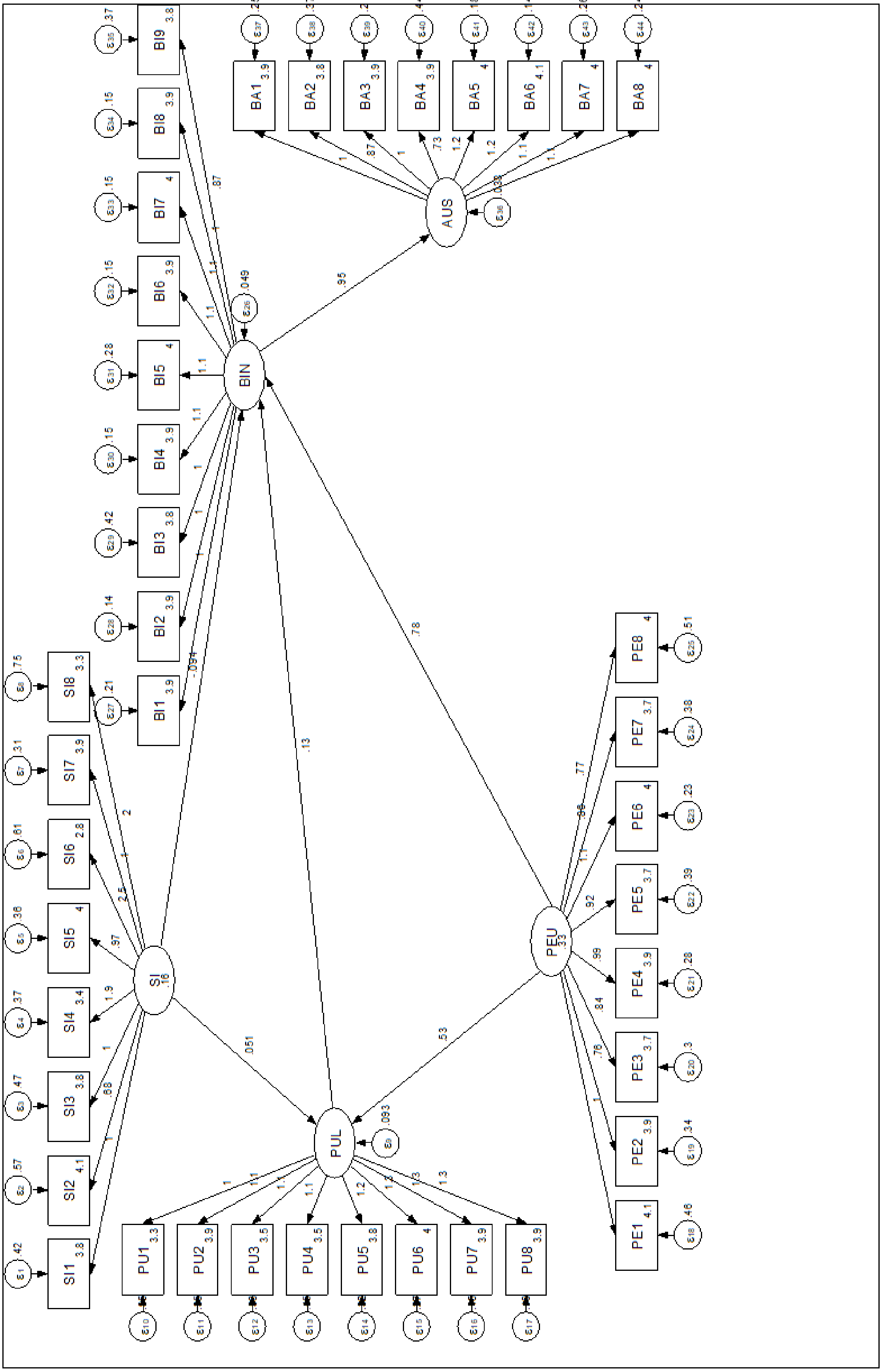

Figure 4.2 The Result of Proposed Research Model (Standarized Estimates)

Source: Survey Data (2023)

4.5.2.1 Assessment of Structural Model

The coefficient of determination (R^2 value) measure is basically used to check the structural model. In addition, this coefficient helps determine the predictive accuracy of the model. It is handled as the squared correlation between actual and predicted values of some endogenous construct. The coefficient means the combined influence of the exogenous latent variable on the endogenous latent variable. Since the squared correlation between the true and predicted values of the variables is presented by the coefficient, the degree of variance of the exogenous constructs identified with it consists of the extent to which every exogenous construct identified with it is protected. Chin (1998), R^2 values greater than 0.67 are high acceptable, qualities between 0.33 and 0.67 are direct, and qualities between 0.19 and 0.33 are weak values. R^2 values lower than 0.19 are unacceptable. In Table 4.9 and Figure 4.3, it can be observed that the model has high predictive power, which supports almost 64.56% and 71.91% variance in behavioral intention to use social media and behavior adoption of social media respectively.

Table 4.9 Coefficient of Determination

Constructs	R^2	Results
Behavioral Intention to Use Social Media	0.6456	High
Actual Usage of Social Media	0.7191	High

R^2 of the Endogenous Latent Variables

Source: Survey Data (2023)

4.5.2.2 Test of The Hypotheses - Path Coefficient

To test the proposed hypotheses, a structural equation model using PLS-SEM with the maximum likelihood estimation was used to assess the relationships among the theoretical constructs for the structural model. As shown in Table 4.10 and Figure 4.3, five out of the six hypotheses are significant. Based on the data analysis, hypotheses H_1, H_2, H_3, H_4, H_5, and H_6 were supported by the empirical data. The results showed that Perceived Usefulness (PUL) significantly influenced Social Influence (SI) ($\beta = 0.076$, $P < 0.10$) and significantly influenced Perceived Ease of Use (PEU) ($\beta = 0.543$, $P < 0.001$) supporting hypotheses $H_1$and H_2 respectively. Behavioral Intention to use Social medias (BIN) was determined to be significant in affecting Perceived Usefulness (PUL) ($\beta = 0.213$, $P < 0.001$) and Perceived Ease of

Use (PEU) (β = 0.692, P < 0.001) supporting hypotheses H_3 and H_5, respectively. Furthermore, Actual usage of social media (AUS) was significantly influenced by Behavioral Intention to use Social Media (BIN) (β = 0.867, P < 0.001) which supports hypothesis H_6. The relationship between Social Influence (SI) and Behavioral Intention to use Social Media (β = -0.060, P < 0.10) is statistically significant, and hypothesis H_4 is, hence, generally supported. A summary of the hypotheses testing results is presented in Table 4.14 and Figure 4.3.

Table 4.10 Results of Structural Model - Research Hypotheses

H	Relationship	Path	z-value	p-value	Direction	Decision
H_1	Social Influence->Perceived Usefulness	0.076	1.81	0.070	Positive	Supported**
H_2	Perceived Ease of Use ->Perceived Usefulness	0.543	12.23	0.000	Positive	Supported**
H_3	Perceived Usefulness->Behavioral Intention to use Social Media	0.213	5.32	0.000	Positive	Supported**
H_4	Social Influence ->Behavioral Intention to use Social Media	-0.060	-1.88	0.060	Negative	Supported**
H_5	Perceived Ease of Use->Behavioral Intention to use Social Media	0.692	17.44	0.000	Positive	Supported**
H_6	Behavioral Intention to use Social Media -> Actual Usage of Social Media	0.867	29.93	0.000	Positive	Supported**

Source: Survey Data (2023)

Significant at p**= (<0.01, p* <0.05, p* < 0.10)

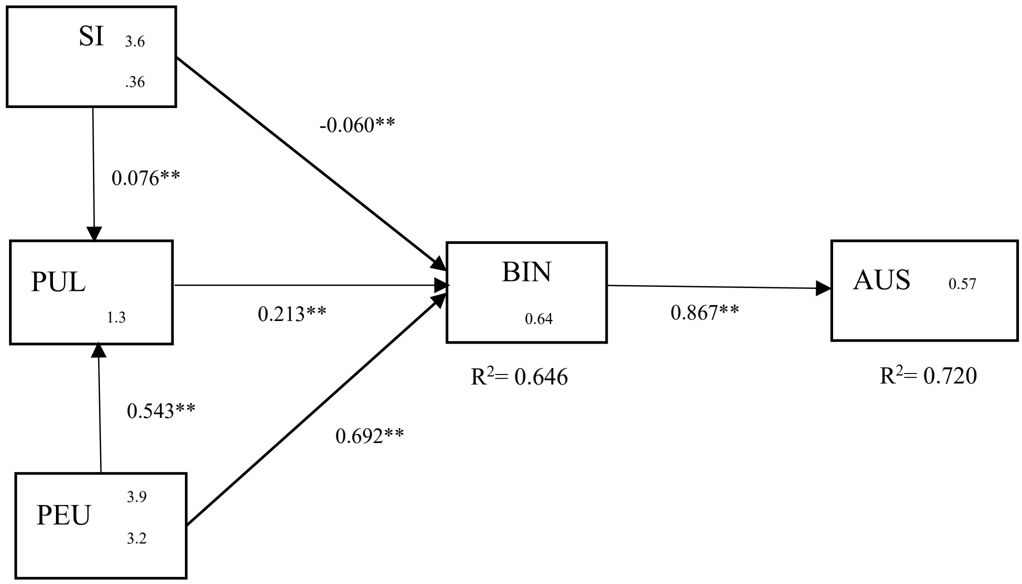

Figure 4.3 Path Coefficient Results (significant at p < = 0.01, p* < 0.05, p* < 0.10)**

Source: Survey Data (2023)

Therefore; all of the hypotheses results are:

H_1. Social influence (SI) have a positive effect on perceived usefulness (PUL).

H_2. Perceived ease of use (PEU) have a positive effect on perceived usefulness (PUL).

H_3. Perceived usefulness (PUL) have a positive effect on behavioral intention to use social media.

H_4. Social influence (SI) have a negative effect on behavioral intention to use social media (BIN).

H_5. Perceived ease of use (PEU) have a positive effect on behavioral intention to use social media.

H_6. The behavioral intention to use social media (BIN) have a positive effect on the actual usage of social media (or) behavior adoption of social media (AUS).

CHAPTER V
CONCLUSION

This chapter presents the findings and discussions for adoption of social media usage among students in YUEco (YTG Campus). This chapter also provides recommendations based on the findings and needs for further research.

5.1 Findings and Discussions

This study investigated the adoption of social-media usage among students in YUEco (YTG Campus). The investigation was carried out to explore if students are comfortable while using social media networking systems, whether they are able to search information on these social media networking systems and whether they perceive social media as an efficient and comfortable way to study and learn various course contents. The Technology Acceptance Model (TAM) constructs were implemented to assess these factors; namely ' Behavior Adoption of Social Media', 'Perceived ease of use', 'Behavioral Intention to use Social Media', 'Perceived Usefulness' and 'Social Influence'. The study revealed that the 'Perceived Ease of Use' and 'Perceived Usefulness' are important factors for predicting a student's behavioral intention to use social media for e-learning in the (YTG Campus), Yangon University of Economics higher education context. Data from personal interviews were analyzed to determine what factors related the causes and effects of social media actual usages on students. The quantitative response of 350 university students were analyzed in this study. Descriptive Analysis, Factor Analysis, Confirmatory Factor Analysis and Structural Equation Modeling (SEM) have been applied to assess the causes and effects of social media actual usage in this study.

In this study, 21.4% of respondents are male students and 78.6% of respondents are female students. Almost 27.7% are age of 19 years, followed by 18 years with 22.9%, 20 years with 18.3%, 21 years with 10.9%, 23 years with 8.9%, 22 years with 8.3% and 17 years with 2.9% while the least were respondents of 24 years with 0.3%. Mean value of age is 19.73 and standard deviation is 0.087. Almost 36% of the students use Facebook and these social media is by far the favorite among students. Next, Twitter and Instagram are the second and third popular LinkedIn and

Tik Tok. 23.1% of students use Twitter and Instagram 12.6% of students use Linked In. Only 5.1% of students use Tik Tok.

In factor analysis, 41 items of the effects of social media and social media usage among 41 items reduced to five constructs: social influence, perceived usefulness, perceived ease of use, behavioral intention to use social medias, actual usage of social medias. Social influence (Factor 1) contains eight items about social media usages for learning new things, achievements, observing others, social norms, like doing people too, act others people, working alone, against others. Perceived usefulness (Factor 2) loads with eight items. These items are social media usefulness such as accomplish tasks, studies/research, better position, increases productivity, improve academic performance, share knowledge, increases knowledge and useful in education. Perceived ease of use (Factor 3) consists of eight items that are ease of use of social media usage. These items are included easy of social media using, clear and understandable, learning to operate easy, find easy to use, learn anything, information easily accessible, public interest easily identified, use without expert help. Behavioral intention to use social medias (Factor 4) consist of nine items about intention to use social medias for knowledge sharing, obtain information and new technology, connect with friends, adopt social media, connect with international cultures, continue using social media, begin or continue using, plan to continue using and recommend others to use. Actual usage of social media (Factor 5) contains eight items such as accepted and used by everyone, increasing means of social engagement, using for educational Purposes, seeing someone's interesting post triggers cravings, keeping what's happening in the world, reconnect with old friends, businesses around the world, connecting with people who share interests.

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 0.811 to 0.925 for the five factors. The Cronbach's alpha reliability coefficient was calculated as 0.942 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 0.940 and Bartlett's Test of Sphericity was 8662.04, which was significant at 1%

level. From the eigenvalues and the scree plot, this trend is observed from the five factors. Their eigenvalues are greater than catch this first five factors were obtained.

In confirmatory factor analysis, overall factors (social influence, perceived usefulness, perceived ease of use, behavioral intention to use social medias, actual usage of social medias) 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 overall factors are greater than 0.8. Therefore, the variance and covariance overall factor are from 90.8% to 100% explained by the model and that are fit acceptably. The comparative of fit indices for overall factors are greater than 0.8. The standardized root mean square residual for overall factors are less than 0.10. Therefore, the incremental fit values and the adequate fit values for overall factors are within acceptable fit. Their models are fit acceptably.

This study proposes a model that investigates the adoption of social media usage among students in Yangon University of Economics (Ywar Thar Gyi Campus). This model was constructed by depending on the findings of previous literature and tested by structural equation modeling. The basic Technology Acceptance Model was applied on social media usage of students for educational Purposes and the effects the university students' in the considering their intension of using social medias were examined. Then, the effects the factors that lead to social medias adoption influencing the intension of the university students were examined. Finally, the overall effects of students' intensions of adopting the use of social medias were determined.

The current study also indicated the rise in the students' behavioral intention to use social media occurred owing to the perceived usefulness, and perceived ease of use. There is a positive effect of perceived usefulness and perceived ease of use on students' behavioral intention to use social media which supports H_1, H_2, H_3, H_5, and H_6. Therefore, behavioral intention to use social medias and actual usage of social medias are used by students in the perceived usefulness for social media and perceived ease of use for social media. Moreover, there is a negative effect of social influence (SI) on students' behavioral intention to use social media which supports H_4. Hence, behavioral intention to use social media not used by students in the social influence. The importance of students' capability and confidence in using social media is indicated in the research. Previously, several studies presented that there was a positive effect of perceived usefulness, social influence, and perceived ease of use on students’ behavioral intention to use social media technology (Salloum, et.al (2018) , Pokhrel, (2022), Fernandez, (2017), Boateng, 2016).

A high predictive power R-squared value overall is determined through perceived usefulness, social influence, perceived ease of use assumed by students' behavioral intention to use social media along with both these variables justifying 64.6% (R^2 = 0.646) of the variance in behavioral intention. Students' behavioral intention predicted the actual usage of social media and 71.9% (R^2 = 0.720) of the variance in actual usage of social media was determined by the overall, showing a moderate overall R-squared value. Similarly (Salloum, et.al (2018) also found that R-squared value overall is determined through perceived usefulness, social influence, perceived ease of use assumed by students' behavioral intention to use social media technology along with both these variables justifying 69% (R^2 = 0.687) of the variance in behavioral intention. Students' behavioral intention predicted the user behavior and 42.3% (R^2 = 0.423) of the variance in User behavior was determined by the overall, showing a moderate overall R-squared value. The present study mainly concluded that perceived usefulness, and perceived ease of use positively influence students' behavioral intention to use social media. Thus, for the student to efficiently develop and implement successful social media applications, the legislators and managers of social media applications are encouraged to essentially put more focus on the factors that are crucial to motivate learning.

5.2 Recommendations

The findings of this study have positively significant effect of perceived usefulness and perceived ease of use on students' behavioral intention to use social media which supports H_1, H_2, H_3, H_5, and H_6. Therefore, empower students in effectively utilizing social media for learning, educational institutions should offer comprehensive training and support. This research investigated TAM with collaboration and resource sharing variables. The research could provide an avenue for future researchers to examine the collaboration and resource sharing in other theoretical frameworks of technological acceptance model. Managerially, the research should be utilized to formulate educational policy to increase the engagement of students in teaching and learning. Likewise, the higher educational institution could apply social media as a source of collaboration and resource sharing to facilitate learning process in business schools. Finally, the factors that influence students' adopting social media platforms for learning should be considered by students, lecturers, and higher education institutions in addressing the challenges confronting the adoption of the platforms as a learning channel.

5.3 Needs for Further Studies

The study recommends that more research should be carried out on the adoption of social media usage among students in Yangon University of Economics (Ywar Thar Gyi Campus). In the future, studies should be carried out to understand the role of student's culture in adopting social media platforms as a learning tool adopting. Likewise, survey research designs and longitudinal studies have been utilized in this study. In future, cross-sectional correlation research designs and experimental research designs can be used to capture variables in meaningful ways. Additionally, the quantitative research method could be employed to measure Collaboration, Resource Sharing, Perceived Usefulness, Perceived Ease of Use and Behavior Intention among undergraduate students. These variables are all subjective, indicating that the use of such methods may not properly reflect the perception or view of students. Therefore, qualitative or mixed methods could be used to explore the phenomena of interest in a more meaningful way.

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Survey Questionnaire

ADOPTION OF SOCIAL MEDIA USAGE AMONG STUDENTS IN YANGON UNIVERSITY OF ECONOMICS (YWAR THAR GYI CAMPUS)

Section(A)

1.Age. ------- years.

2.Gender

- Male
- Female

3. Current residence. Do you live in a hostel?

- Yes
- No

4. Religion

- Buddhism
- Christian
- Islan
- Others........

5. Ethnic

- Burmese
- Kayin
- Rakhine
- Mon
- Shan
- Kachin
- Kayah
- Chin
- Other

6. State / Region

- Kachin
- Kayah
- Kayin
- Chin

- Mon
- Rakhine
- Shan
- Yangon
- Mandalay
- Nay Pyi Taw
- Bago
- Magwe
- Sagaing
- Tanintharyi
- Ayeyarwady

7. What is your specialization?

- B.Com
- B.Act
- BBA
- B.Econ(Stats)
- BPS
- B.Econ(Eco)
- B.Dev.S
- BPA

8. Which academic year are you attended in university?

- First year
- Second year (First semester)
- Second year (Second semester)
- Third year/H_1
- Final year/H_2/H_3 and Qualified

Section(B)

9. Which social media that you use more?

- Facebook
- Twitter
- Instagram
- Linked In

- TikTok
- Others........

10. How often do you use social media in a day?
    - Less than 1 hour
    - 1-3 hours
    - 3-5 hours
    - 5-7 hours
    - Seven hours or more

Section(C)

11. Please indicate your answer. (choose one)

1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree
4. Agree 5. Strongly Agree

S/N	Items	1	2	3	4	5
1.	**Social Influence**					
	1. I prefer learning new things by watching others.					
	2. I enjoy when my achievements are acknowledged in public.					
	3. To improve my skills, I learn best by observing others.					
	4. Social norms I prefer to do what other people typically do.					
	5. When I see people doing something I'm interested in, I feel like doing it too.					
	6. I prefer to act the way everyone else is acting.					
	7. I enjoy working with other people, rather than working alone.					
	8. I assess my performance against others.					
2.	**Perceived Usefulness**					
	1. Using social media enables me to accomplish tasks more quickly.					
	2. I find social media useful in my studies/research.					
	3. If I use social media, it will increase my chances of getting a better position.					
	4. Using social media increases my productivity.					

	5. I engage in academic discussions on social media and improve my academic performance.					
	6. I found social media is a useful place to share knowledge with my classmates.					
	7. Using social media increases knowledge.					
	8. I think that the social media are useful in my education.					
3.	**Perceived Ease of Use**					
	1. It is easy for me to become skillful at using social media.					
	2. My interaction with social media is clear and understandable.					
	3. Learning to operate social media is easy for me.					
	4. I find social media easy to use.					
	5. Social-media makes it easy for me to learn anything.					
	6. Information is easily accessible.					
	7. public interest on new data for engagement and behavior can be easily identified.					
	8. I think that it is possible to use the social media without expert help.					
4.	**Behavioral Intention to Use Social Media**					
	1. I predict that I would adopt social media for knowledge sharing.					
	2. We intend to use social media to obtain information and new technology.					
	3. I will always try to use social media to keep track of my daily life activities and connect with friends.					
	4. I intend to adopt social media for knowledge sharing.					
	5. It is predicted that social media will be used to connect with international cultures in the future.					
	6. I will continue using social media for knowledge sharing.					

	7. I intend to begin or continue using the social media I will frequently use social media in the future.					
	8. I plan to continue using social media for knowledge sharing.					
	9. I will recommend others to use the social media.					
5.	**Actual Usage of Social media (or) Behavior Adoption of Social Media**					
	1. The use of social media has become accepted and used by everyone.					
	2.The use of social media has been increasing means of social engagement.					
	3. Social-media is useful for educational purposes.					
	4. When you see someone's interesting post on social media, it triggers your cravings.					
	5. Using social media can keep you in touch with what's happening in the world.					
	6. You can reconnect with old friends through social media.					
	7. Social-media is an essential tool for businesses around the world.					
	8. I can connect with people who share my interests on social media.					

APPENDIX

Factor Analysis

[DataSet1] C:\Users\USER\Desktop\Social media SPSS-Stata.sav

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.940
Bartlett's Test of Sphericity	Approx. Chi-Square	8662.040
	df	820
	Sig.	.000

Communalities

	Initial	Extraction
SI-1	1.000	.649
SI-2	1.000	.582
SI-3	1.000	.587
SI-4	1.000	.670
SI-5	1.000	.431
SI-6	1.000	.715
SI-7	1.000	.514
SI-8	1.000	.530
PU-1	1.000	.512
PU-2	1.000	.507
PU-3	1.000	.540
PU-4	1.000	.611
PU-5	1.000	.512
PU-6	1.000	.508
PU-7	1.000	.677
PU-8	1.000	.636
PE-1	1.000	.610
PE-2	1.000	.533
PE-3	1.000	.533
PE-4	1.000	.544
PE-5	1.000	.394
PE-6	1.000	.618
PE-7	1.000	.435
PE-8	1.000	.398
BI-1	1.000	.616
BI-2	1.000	.692
BI-3	1.000	.474
BI-4	1.000	.674
BI-5	1.000	.592
BI-6	1.000	.687
BI-7	1.000	.702
BI-8	1.000	.683
BI-9	1.000	.526
BA-1	1.000	.582
BA-2	1.000	.438
BA-3	1.000	.622
BA-4	1.000	.431
BA-5	1.000	.683
BA-6	1.000	.702
BA-7	1.000	.581
BA-8	1.000	.608

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	14.936	36.429	36.429	14.936	36.429	36.429	11.703	28.543	28.543
2	3.592	8.760	45.188	3.592	8.760	45.188	3.572	8.713	37.256
3	2.260	5.513	50.701	2.260	5.513	50.701	3.212	7.834	45.090
4	1.509	3.682	54.383	1.509	3.682	54.383	3.072	7.493	52.583
5	1.239	3.022	57.405	1.239	3.022	57.405	1.977	4.822	57.405
6	1.160	2.829	60.235						
7	.975	2.379	62.614						
8	.939	2.291	64.905						
9	.908	2.214	67.119						
10	.823	2.008	69.127						
11	.813	1.982	71.110						
12	.759	1.851	72.961						
13	.695	1.695	74.655						
14	.673	1.641	76.296						
15	.664	1.620	77.917						
16	.590	1.438	79.355						
17	.588	1.433	80.788						
18	.558	1.360	82.148						
19	.519	1.267	83.414						
20	.511	1.247	84.662						
21	.474	1.155	85.817						
22	.441	1.077	86.894						
23	.432	1.053	87.946						
24	.420	1.025	88.971						
25	.394	.961	89.931						
26	.381	.929	90.860						
27	.376	.916	91.776						
28	.341	.832	92.609						
29	.329	.803	93.411						
30	.320	.780	94.192						
31	.296	.723	94.915						
32	.276	.673	95.588						
33	.266	.648	96.236						
34	.249	.608	96.844						
35	.232	.565	97.409						
36	.217	.530	97.939						
37	.203	.495	98.434						
38	.186	.454	98.888						
39	.168	.409	99.297						
40	.154	.375	99.672						
41	.135	.328	100.000						

Extraction Method: Principal Component Analysis.

	Component				
	1	2	3	4	5
BI-2	.811				
BI-7	.809				
BA-6	.809				
BI-4	.809				
BI-6	.802				
BA-5	.793				
BI-8	.787				
BA-3	.776				
PE-6	.766				
BI-1	.762				
BA-8	.740				
BI-5	.719				
BA-1	.712				
BA-7	.707				
PE-4	.687				
PU-8	.655		.391		
PU-7	.642		.466		
PE-1	.640				-.326
BI-3	.636				
PE-7	.625				
PE-5	.621				
PE-3	.619				
BI-9	.613				.324
BA-2	.610				
PU-6	.608		.356		
PE-2	.573			-.347	
PU-2	.556		.421		
PU-5	.531		.396		
PE-8	.511				
BA-4	.488				
SI-6		.760			
SI-4		.747			
SI-8		.694			
SI-7		.621			
SI-5		.601			
SI-3		.561		.309	-.317
SI-1		.554		.349	-.303
PU-3	.406		.576		
PU-4	.453		.540		
PU-1			.485		.383
SI-2		.381		.577	

Extraction Method: Principal Component Analysis.

a. 5 components extracted.

Rotated Component Matrixa

	Component				
	1	2	3	4	5
BA-6	.805				
BI-7	.794				
BA-5	.780				
BI-4	.765				
BI-2	.765				
BI-6	.760				
BA-8	.756				
BI-8	.752				
BA-1	.747				
BA-7	.739				
BA-3	.725				
PE-6	.717				
BI-1	.711			.305	
BI-5	.671				
BI-9	.620	.356			
BA-2	.618				
BI-3	.615				
PE-7	.600				
PE-4	.589			.431	
PE-5	.553				
BA-4	.536				
PE-8	.522				
PU-4		.737			
PU-3		.695			
PU-1		.668			
PU-2	.359	.586			
PU-7	.309	.562		.509	
PU-5		.487		.447	
PU-6	.362	.472		.382	
SI-6			.830		
SI-4			.796		
SI-8			.701		
SI-5			.647		
SI-7			.597		.314
PE-1	.384			.630	
PE-2	.360			.614	
PE-3	.423			.554	
PU-8	.365	.485		.517	
SI-2					.726
SI-1			.371		.683
SI-3			.343		.651

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 7 iterations.

Rotated Factor Matrix[a]

	Component				
	1	2	3	4	5
SI-1	.683				
SI-2	.726				
SI-3	.651				
SI-4	.796				
SI-5	.647				
SI-6	.830				
SI-7	.597				
SI-8	.701				
PU-1		.668			
PU-2		.586			
PE-3		.695			
PU-4		.737			
PU-5		.487			
PU-6		.472			
PU-7		.562			
PU-8		.517			
PE-1			.630		
PE-2			.614		
PE-3			.554		
PE-4			.589		
PE-5			.553		
PE-6			.717		
PE-7			.600		
PE-8			.522		
BI-1				.711	
BI-2				.765	
BI-3				.615	
BI-4				.765	
BI-5				.671	
BI-6				.760	
BI-7				.794	
BI-8				.752	
BI-9				.620	
BA-1					.747
BA-2					.618
BA-3					.725
BA-4					.534
BA-5					.780
BA-6					.805
BA-7					.739
BA-8					.756

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

Component Transformation Matrix

Component	1	2	3	4	5
1	.862	.333	.090	.349	.129
2	-.248	.141	.870	.108	.388
3	-.383	.863	-.247	.209	-.062
4	.089	.157	-.264	-.577	.752
5	.205	.315	.323	-.700	-.514

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

Reliability Statistics

Cronbach's Alpha	N of Items
.942	41

Correlations

		SI	PUL	PEU	BIN	AUS
SI	Pearson Correlation	1	.206**	.227**	.135*	.142**
	Sig. (2-tailed)		.000	.000	.011	.008
	N	350	350	350	350	350
PUL	Pearson Correlation	.206**	1	.568**	.581**	.530**
	Sig. (2-tailed)	.000		.000	.000	.000
	N	350	350	350	350	350
PEU	Pearson Correlation	.227**	.568**	1	.784**	.772**
	Sig. (2-tailed)	.000	.000		.000	.000
	N	350	350	350	350	350
BIN	Pearson Correlation	.135*	.581**	.784**	1	.848**
	Sig. (2-tailed)	.011	.000	.000		.000
	N	350	350	350	350	350
AUS	Pearson Correlation	.142**	.530**	.772**	.848**	1
	Sig. (2-tailed)	.008	.000	.000	.000	
	N	350	350	350	350	350

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

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

Reliability Statistics

Cronbach's Alpha	N of Items
.811	8

Reliability Statistics

Cronbach's Alpha	N of Items
.842	8

Reliability Statistics

Cronbach's Alpha	N of Items
.857	8

Reliability Statistics

Cronbach's Alpha	N of Items
.925	9

Reliability Statistics

Cronbach's Alpha	N of Items
.903	8

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	PEU, SI, PUL[b]	.	Enter

a. Dependent Variable: BIN
b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.804[a]	.646	.643	.34402

a. Predictors: (Constant), PEU, SI, PUL

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	74.729	3	24.910	210.479	.000[b]
	Residual	40.948	346	.118		
	Total	115.677	349			

a. Dependent Variable: BIN
b. Predictors: (Constant), PEU, SI, PUL

Coefficients[a]

Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1 (Constant)	.646	.162		3.980	.000
SI	-.060	.032	-.062	-1.885	.060
PUL	.213	.040	.207	5.299	.000
PEU	.693	.040	.681	17.351	.000

a. Dependent Variable: BIN

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	BIN[b]	.	Enter

a. Dependent Variable: AUS

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.848[a]	.720	.719	.31182

a. Predictors: (Constant), BIN

ANOVA[a]

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	86.918	1	86.918	893.956	.000[b]
Residual	33.836	348	.097		
Total	120.754	349			

a. Dependent Variable: AUS

b. Predictors: (Constant), BIN

Coefficients[a]

Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1 (Constant)	.564	.114		4.938	.000
BIN	.867	.029	.848	29.899	.000

a. Dependent Variable: AUS

```
. regress AUS BIN

      Source |       SS       df       MS              Number of obs =     350
-------------+------------------------------           F(  1,   348) =  890.76
       Model |  86.8588765     1  86.8588765           Prob > F      =  0.0000
    Residual |  33.9338789   348  .097511146           R-squared     =  0.7191
-------------+------------------------------           Adj R-squared =  0.7183
       Total |  120.792755   349  .346111047           Root MSE      =  .31227

------------------------------------------------------------------------------
         AUS |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         BIN |   .8665784   .0290354    29.85   0.000     .8094715    .9236854
       _cons |   .5672947   .1145002     4.95   0.000     .3420952    .7924942
------------------------------------------------------------------------------

. regress BIN SI PUL PEU

      Source |       SS       df       MS              Number of obs =     350
-------------+------------------------------           F(  3,   346) =  210.07
       Model |  74.6686243     3  24.8895414           Prob > F      =  0.0000
    Residual |  40.9954445   346  .118483944           R-squared     =  0.6456
-------------+------------------------------           Adj R-squared =  0.6425
       Total |  115.664069   349   .33141567           Root MSE      =  .34421

------------------------------------------------------------------------------
         BIN |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          SI |  -.0592449   .0317089    -1.87   0.063    -.1216113    .0031215
         PUL |   .2128091   .0402225     5.29   0.000     .1336978    .2919204
         PEU |   .6924359   .0399401    17.34   0.000       .61388    .7709917
       _cons |   .6445587   .1625051     3.97   0.000     .3249365     .964181
------------------------------------------------------------------------------
Fitting target model:

Iteration 0:   log likelihood = -1037.1458
Iteration 1:   log likelihood = -1037.1458  (backed up)

Structural equation model                       Number of obs      =       350
Estimation method  = ml
Log likelihood     = -1037.1458

------------------------------------------------------------------------------
             |                 OIM
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Structural   |
  PUL <-     |
          SI |   .0758693   .0419428     1.81   0.070    -.0063371    .1580756
         PEU |   .5433065   .0444273    12.23   0.000     .4562305    .6303824
       _cons |   1.333924   .2038453     6.54   0.000     .9343945    1.733453
  -----------+----------------------------------------------------------------
  BIN <-     |
         PUL |   .2128091    .039992     5.32   0.000     .1344263    .2911919
          SI |  -.0592449   .0315271    -1.88   0.060     -.121037    .0025472
         PEU |   .6924359   .0397112    17.44   0.000     .6146034    .7702683
       _cons |   .6445587   .1615739     3.99   0.000     .3278797    .9612377
  -----------+----------------------------------------------------------------
  AUS <-     |
         BIN |   .8665784   .0289523    29.93   0.000     .8098329    .9233239
       _cons |   .5672947   .1141726     4.97   0.000     .3435206    .7910689
-------------+----------------------------------------------------------------
   var(e.PUL)|   .2092444   .0158174                      .1804301    .2426602
   var(e.BIN)|   .1171298   .0088542                      .1010003    .1358352
   var(e.AUS)|   .0969539    .007329                      .0836028    .1124373
------------------------------------------------------------------------------
LR test of model vs. saturated: chi2(3)   =     38.91, Prob > chi2 = 0.0000
```

```
. estat gof, stats(chi2 rmsea indices residuals)
```

Fit statistic	Value	Description
Likelihood ratio		
chi2_ms(773)	1990.645	model vs. saturated
p > chi2	0.000	
chi2_bs(820)	9065.834	baseline vs. saturated
p > chi2	0.000	
Population error		
RMSEA	0.067	Root mean squared error of approximation
90% CI, lower bound	0.000	
upper bound	.	
pclose	.	Probability RMSEA <= 0.05
Baseline comparison		
CFI	0.852	Comparative fit index
TLI	0.843	Tucker-Lewis index
Size of residuals		
SRMR	0.082	Standardized root mean squared residual
CD	0.988	Coefficient of determination

.

Frequencies

Statistics

		Age	Gender	Current Residence	Religion	Major Specialization	Attendence year	Use of social media more	Use social media in a day
N	Valid	350	350	350	350	350	350	350	350
	Missing	0	0	0	0	0	0	0	0

Frequency Table

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	17	10	2.9	2.9	2.9
	18	80	22.9	22.9	25.7
	19	97	27.7	27.7	53.4
	20	64	18.3	18.3	71.7
	21	38	10.9	10.9	82.6
	22	29	8.3	8.3	90.9
	23	31	8.9	8.9	99.7
	24	1	.3	.3	100.0
	Total	350	100.0	100.0	

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	75	21.4	21.4	21.4
	Female	275	78.6	78.6	100.0
	Total	350	100.0	100.0	

Current Residence

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	199	56.9	56.9	56.9
	No	151	43.1	43.1	100.0
	Total	350	100.0	100.0	

Religion

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Buddhism	336	96.0	96.0	96.0
	Christian	8	2.3	2.3	98.3
	Islan	5	1.4	1.4	99.7
	Others	1	.3	.3	100.0
	Total	350	100.0	100.0	

Major Specialization

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	B.com	88	25.1	25.1	25.1
	BAt	20	5.7	5.7	30.9
	BBA	46	13.1	13.1	44.0
	B.Econ(Stats)	64	18.3	18.3	62.3
	BPS	11	3.1	3.1	65.4
	B.Econ(Eco)	23	6.6	6.6	72.0
	B.Devs	41	11.7	11.7	83.7
	BPA	57	16.3	16.3	100.0
	Total	350	100.0	100.0	

Attendance year

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	First year	163	46.6	46.6	46.6
	Second year (First semester)	49	14.0	14.0	60.6
	Second year (Second semester)	60	17.1	17.1	77.7
	Third year/H1	28	8.0	8.0	85.7
	Final year/H2	50	14.3	14.3	100.0
	Total	350	100.0	100.0	

Use of social media more

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Facebook	126	36.0	36.0	36.0
	Twitter	81	23.1	23.1	59.1
	Instagram	81	23.1	23.1	82.3
	Linked In	44	12.6	12.6	94.9
	Tik Tok	18	5.1	5.1	100.0
	Total	350	100.0	100.0	

Use social media in a day

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 1 hour	22	6.3	6.3	6.3
	One hour Less than three hours	145	41.4	41.4	47.7
	Three hours Less than five hours	111	31.7	31.7	79.4
	Five o'clock and under seven o'clock	53	15.1	15.1	94.6
	Seven hours or more	19	5.4	5.4	100.0
	Total	350	100.0	100.0	