THE IMPACT OF SELF-EFFICACY, PERSONAL INNOVATIVENESS AND CONTENT QUALITY ON USING MOBILE-LEARNING IN HIGHER VOCATIONAL COLLEGES: EVIDENCE FROM CHINA

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ABSTRACT

The advent of internet technology has led to a surge in interest in mobile learning, particularly among students in higher vocational colleges. Despite this growing interest, there are still some challenges such as low usage rate and unsatisfactory effect of mobile learning among students in higher vocational colleges in China. Therefore, this study aims to investigate how to enhance students' intention to use mobile learning in Chinese higher vocational colleges. The extended Unified Theory of Acceptance and Use of Technology (UTAUT) model was employed to investigate the factors influencing the intention and use behavior of mobile learning among Chinese vocational college students. Three variables of self-efficacy, personal innovativeness, and content quality were incorporated. A total of 636 higher vocational college students in seven regions of China were selected, and there was little difference in the prior knowledge level of all students. Analysis was done using confirmatory factor analysis (CFA) and structural equation modeling (SEM).This study demonstrates that self-efficacy, personal innovativeness, and content quality have a positive and significant impact on the use of mobile learning based on the UTAUT model. Additionally, self-efficacy has a significant impact on the four constructs of UTAUT model. The findings of this research can help higher vocational colleges to better understand the

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mobile learning implementation and benefit decision makers, designers, and developers to ensure that students participate actively in using mobile learning platforms. The colleges should consider important strategies related to effort performance, social influence, content quality and self-efficacy in order to improve the adoption of mobile learning systems among students.

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CHAPTER 1

INTRODUCTION

1.1 Background and Research Significance

The rapid development of computer technology and wireless network communication technology in the 21st century has changed people's way of life. The emergence of wireless network communication technology provides strong technical support for the development of mobile learning, and have a deep impact on teaching and learning methods. With the development of mobile communication technology, mobile learning has become an important medium of higher education, bringing more learning experience for students (Almaiah et al., 2022). According to an Internet research report from QuestMobile, the number of mobile phone users in 2022 is 1.2 billions in China. In both developed and developing countries, the mobile industry has experienced rapid growth, with rapid and steady growth in personal ownership (Dias & Victor, 2022). Through mobile devices such as mobile phones and tablets, students can get the learning resources they need anytime and anywhere. With the popularization of network infrastructure, the cost of using mobile Internet equipment and technology is also decreasing, which is also regarded as a necessary condition to promote mobile learning (Li et al.,2021). Common mobile devices such as mobile phones and tablet computers are very popular among students, and students' thinking patterns and learning habits are also influenced by them. Many studies have shown that mobile learning has enriched traditional teaching modes, and more and more classrooms have adopted mobile devices to distribute learning materials or supplement teaching, achieving positive learning results (Almaiah et al., 2022; Lutfi et al., 2022; Chao, 2019). And during the epidemic of COVID-19, mobile learning played an irreplaceable role in maintaining the normal teaching process and ensuring students' right to education (Zhang et al., 2020).

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In China's during the Covid-19, Ministry of Education proposed to "suspend classes and continue learning", and e-learning and mobile learning provided solutions. Most universities and colleges use live online learning to keep up with teaching. Students cannot go back to school on time and can only study online courses at home. In the transformation process of education, active teaching methods and technology incorporation into learning surroundings become inevitable. By this chance, The Ministry of Education has organized 22 online course platforms to provide free access to more than 24,000 online courses. All colleges and universities have formulated effective plans to carry out online learning by relying on high-quality online course resources. According to the statistics of UNESCO, China is the country with the strongest implementation capacity of online learning during the epidemic, and online learning has ushered in an outbreak opportunity. Most of the courses on government-enterprise cooperative online education platforms are open to the public, including Chinese university students MOOC, Wisdom Tree, Xuetang Online, etc. g. After the pandemic outbreak, students can continue studying and learning through remote means, and m-learning has become useful for this purpose. The large-scale online teaching during the epidemic is a deep combination of teaching and modern information technology, which has spawned the rapid development of mobile learning. In this context, the analysis of the factors affecting the mobile learning behavior of students is helpful to promote the process of Internet + education and the integration of online education and offline education.

Mobile learning refers to the use of smart phones, tablet computers and other mobile Internet technology equipment, through the independent selection of learning time, place, environment, content and methods to obtain relevant resources, and finally realize their own learning needs in a new form. Mobile learning and traditional digital learning are not only different, but also closely related. Mobile learning is derived from traditional digital learning and is an extension of traditional digital learning. Mobile learning is flexible in form, and learners are not limited to smart phones or other devices, because the teaching environment, teaching resources and learners can be mobile. A large number of studies have proved that mobile learning has obvious advantages, such as providing more resources, not limited by time and place (Al-Adwan et al., 2018; Almaiah et al., 2022), helping students and teachers establish immediate contact and exchange information (Almaiah & Alismaiel, 2019), and

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making the learning process more fun to stimulate students' learning motivation and responsibility (Ali & Arshad, 2016). Mobile learning has the characteristics of timeliness, flexibility, fragmentation and continuity.

Figure 1.1 The page of the iCourse

Mobile learning, while often considered superior to traditional learning methods, has certain drawbacks when implemented in higher education institutions. For instance, there are concerns regarding the high costs associated with infrastructure construction (Alshurideh et al., 2019) and the lower acceptance rates among students (Krull & Duart, 2017; Almaiah et al.,

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2016). While mobile devices are frequently used by learners to support their work in educational contexts for tasks such as information access and communication, they are not yet considered an essential learning platform. This is due, in part, to the personal nature of mobile devices, which can lead to distractions from other applications and activities, and cause students to overlook them as a dedicated learning platform. Although ownership of mobile devices is high, their usage for learning purposes is not yet widespread (Devourou et al., 2022). Furthermore, studies (Kim et al., 2017; Hamidi & Chavoshi, 2018) have indicated that even though many universities have extended their online learning platforms to include mobile services, students' interest and usage of mobile learning is not as high as anticipated. Differences in platforms and operating systems, as well as the availability and stability of WIFI connections, which many mobile Internet users rely on, can affect a student's ability to access mobile learning resources (Yang et al., 2017). Consequently, despite the availability of apps and mobile-accessible resources, mobile learning remains largely driven by end-users in most cases.

These issues indicate the necessity of this study, which focuses on the influencing factors of intention and usage of mobile learning based on UTAUT model. The UTAUT model has advantages in analyzing technology acceptance as it can explain roughly 70% of the variance (Wijaya et al., 2022). Although the traditional UTAUT model was extensively used, those studies have not considered all essential factors that could play an important role for students' usage of mobile learning.

Thus, the present study extends the UTAUT model by three new factors from two different perspectives---personal perspective and quality perspective. First factor is self-efficacy, which was introduced from Bandura's (1986) social cognitive theory. Bandura (1986) defines the concept of self-efficacy (SE) as the main element of social cognitive theory, which is becoming widespread in areas of education (Islam et al., 2020). Almaiah et al. (2019) declaimed that self-efficacy affected use of mobile learning. Li et al. (2022) incorporated self-efficacy into the UTAUT model and found that self-efficacy has significant influence on effort expectancy, performance expectancy, social influence and facilitating conditions. The other personal factor is Personal Innovativeness, which implies more creative users are more likely to embrace new technology(Hong et al., 2021; Alhussain et al., 2020). The study

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(Alturki & Aldraiweesh, 2022) indicated that behavior intention of mobile learning is positively affected by Personal Innovativeness. Other studies (Prasetyo et al., 2021) maintained that the low level of mobile incorporated learning use and acceptance among students stems from the low quality of m-learning platforms. Among quality factors, content quality can measure the performance and information towards e-learning and m-learning (Alsabawy, 2016). Considering this, we contain one of the quality factor---content quality into our model, which is from the DeLone & McLean (D&M) model (2003). Almaiah et al. (2020) supported that content quality have a significant positive effect on mobile learning adoption in different stages.

The study extended the UTAUT model by including three additional variables - self-efficacy, personal innovativeness and content quality. The study was carried out in China. China is considered appropriate, for it has used the technology and has proved to be beneficial in education. However, it has not fully been integrated into the education system and students' interest and use of mobile learning is not as high as anticipated (Hamidi & Chavoshi, 2018). Therefore, the study contributed significantly towards the use of technology in the education system.

1.2 Research Problems

In China in March 2022, the National Smart Education Platform for Higher Education was officially launched. Created by the Ministry of Education, it is now the largest, most comprehensive and most-used higher education platform in the world, covering 13 disciplines and 92 majors, and offering high-quality courses to university and college teachers, students and social learners. At the same time, it also integrates several online education platforms to further diversify course resources. The emergence of this kind of platform fills the gap in the market and is also an important part of the online education industry. Online education has become a widely accepted and favored way of learning, and mobile terminal based online learning, namely mobile learning, is becoming the development trend of education digitization and lifelong learning. Major educational platforms and content providers, such as Blackboard in America, iCourse and Chaoxing in China, provide free apps for accessing

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courses and course material. Collectively, these conditions suggest that in the near future mobile devices will be widely used to support learning in both formal and informal contexts.

However, many scholars still concerned about the disadvantages of mobile learning, for example, there might be technological difficulties, frustration with the device, time consumption, and antipathetic teachers. Specifically, challenges such as small keypads, network issues, and using smartphones for other purposes than educational, are important concerns that could interfere with learning (Jeno et al., 2017). Some studies suggested some critiques as large investment in infrastructure construction and low acceptance rate, interactive design of mobile learning applications, quality of teaching system. (Yang et al., 2017; Sarrab et al., 2018). Another challenge is the lack of knowledge about mobile learning among students, which can lead to a lack of interest and motivation to use mobile devices for academic usage.

Many researches focus on mobile learning in universities (Abbad, 2021; Lutfi et al. , 2022; Botero et al., 2018), but few in higher vocational colleges. The way students in higher vocational colleges use mobile learning is very different from that in universities. To most university students mobile learning is a voluntary choice, in order to learn more in-depth knowledge, and students to find their own mobile platform for learning. For students in higher vocational colleges, mobile learning mostly comes from the hybrid teaching of the curriculum itself, it is a supplement to the main courses and may take up a certain number of class hours. Even so, students still fail to complete courses on mobile learning platforms. The differences may come from students' personality characteristics. Chinese students in colleges and universities exhibit diverse learning habits, motivations, and abilities. Thus, the two group students have different needs for mobile learning content. It is essential to investigate factors of students in higher vocational colleges using mobile learning, from the perspective of students and content quality (Almaiah et al, 2019). This study can fill in the gap by exploring impacts of the behavior intention and the use of mobile learning in higher vocational colleges by incorporating self-efficacy, personal innovativeness and content quality into UTAUT model.

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1.3 Research Questions

This study uses an extended UTAUT model to explain the acceptance degree of mobile learning among higher vocational college students. We will focus on the following questions:

RQ1: How do self-efficacy, personal innovativeness, and content quality affect the intention and actual use of mobile learning?

RQ2: Based on the extended UTAUT model, what are the main factors affecting the behavioral intention and actual use of mobile learning among Chinese higher vocational students?

RQ3: How can the extended UTAUT model be validated?

1.4 Research Objective

The research objectives are listed as follows:

1) To investigate the effects of self-efficacy, personal innovativeness, and content quality on intention and actual use of mobile learning.

2) To explore the main factors affecting the behavioral intention and actual use of mobile learning.

3) To validate the extended UTAUT model on using mobile learning.

1.5 Scope of Research

Scope of content: Through the collation and review of the literature this study chooses the UTAUT model as basis, including performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention and use behavior. Through research and comparison, this study includes self-efficacy, personal innovativeness and course quality into the UTAUT model.

Variables: The variables are classified into three types: exogenous latent variables, endogenous latent variables, and moderator variables.

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1) The exogenous latent variables including observed variables as listed:

a) Performance expectancy

- Perceived usefulness
- Relative advantage
- Outcome expectation

b) Effort expectancy

- Perceived Ease of Use
- Ease of Use.

c) Social influence

- Subjective Norm
- Social Factors

d) Facilitating conditions

- Perceived Behavioral Control
- Facilitating conditions

e) Self-efficacy

- Confidence
- Capability

f) Personal innovativeness

- Behaviors
- States

g) Content quality

- Informativeness
- Accessibility

2) The endogenous latent variables including observed variables as listed:

a) Behavioral intention

- Intention to use technology
- Planning to use technology
- Prediction to use technology

b) Use behavior

- Preference

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- Frequently use
- Recommendation

Scope of Population: the population of this study is rather large, as contains students in higher vocational colleges in China. The students have some experience in using mobile learning platforms. From this population we obtain the sample for our study.

1.6 Research Benefits

1.6.1 Practical Benefits

Students' acceptance of mobile learning not only affects the occurrence of online learning behavior, but also is an important prerequisite for mobile learning platform to realize its educational value, social value and commercial value. Therefore, the practical benefits of the research mainly includes two aspects: First, the research has certain practical significance for higher vocational colleges. In this study, questionnaire survey was adopted to investigate students' behavioral intention in mobile learning, which can help colleges and teachers better understand the factors affecting students' use of mobile learning, so as to formulate corresponding programs to improve learners' behavioral intention and usage behavior. It is of great practical significance to reform the disadvantages of traditional classroom teaching, promote the transformation of learners' learning methods, improve teaching quality and promote the application of vocational education informatization. Secondly, this study has certain significance for the builders of mobile learning platform. Mobile learning has been used for a long time, why it has not been popularized in a long period of time, colleges do not choose this way in the first place, which shows that mobile learning is facing great challenges. Only targeted improvement of online learning products according to the actual needs of learners can bring better learning experience for learners, so as to stimulate the enthusiasm of learners to use online learning.

1.6.2 Theoretical Benefits

Mobile learning is one of the main form of vocational education in the future. Based on an extended UTAUT model, this study proposes a model of influencing factors of mobile

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learning behavioral intention and use behavior of higher vocational students, which has certain theoretical significance. There are few researches on the behavioral intention and use behavior of mobile learning for higher vocational college students at present. By exploring the influencing factors through modeling, this study can better explain what are the main factors affecting mobile learning of higher vocational college students, and what is the logical relationship between these factors and the degree of influence. It is helpful to enrich the theories related to the modeling of influencing factors of mobile learning, and provide reference variables for the subsequent researches of mobile learning.

1.7 Definition of Terms

1.7.1 Mobile learning

Mobile learning means the acquisition of knowledge with personal mobile devices connected to internet (Almaiah & Alismaiel, 2019).

1.7.2 Use Behavior

Use behavior refers to the extent to which students use mobile phones in the studies as learning tools (Nikolopoulou et al., 2020).

1.7.3 Behavioral intention

Behavioral intention refers to the extent to which students intend to use mobile phones in their studies (Nikolopoulou et al., 2020).

1.7.4 Performance expectancy

Performance expectancy is defined as the degree to which an individual believes mobile learning will lead to better rewards or outcomes in a given task (Kaliisa et al., 2017).

1.7.5 Effort expectancy

Effort expectancy refers to the amount of ease that students expect to feel when using mobile learning system (Shaya et al., 2023).

1.7.6 Social influence

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Social influence refers to the level to which end users viewed significant others (e.g., family and friends) think that they should utilize mobile learning (Yee & Abdullah, 2021).

1.7.7 Facilitating conditions

Facilitating conditions refers to the degree to which students perceive that the institutional and technical infrastructures are available to support the use of mobile learning (Lwoga & Komba, 2015).

1.7.8 Self-efficacy

Self-efficacy refers to an individual's judgment of his/her capacity to perform a learning task through mobile learning systems. The belief in the ability to fulfill an educational task with the use of e-learning systems (Sahin et al., 2022).

1.7.9 Personal Innovativeness

Personal Innovativeness refers to willingness of an individual to accept innovation earlier than others in terms of mobile learning (Kim, Lee, Rha, 2017), which is attached with trying new features and advancements.

1.7.10 Content quality

Content quality refers to the extent to which complete, accurate, organized, understandable, up to date, and timely information is provided in mobile learning application for users to obtain information about any of their intended services (Almaiah et al., 2020).

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CHAPTER 2

LITERATURE REVIEW

The research objective is to develop a model of usage of mobile learning in China. It incorporates the previous literature review related to the topic and the theories grounding the study. Then the conceptual framework is given. The guideline of this chapter is as follows.

2.1 Mobile Learning Overview

In modern society, information and mobile communication technology are rapidly developing. Whether willing or not, our life is influenced and changed by the new development in various ways. Mobile smart devices have been given a lot of marvelous function with the help of information and mobile communication technology. According to an Internet research report from QuestMobile, the number of mobile phone users in 2022 is 1.2 billion. The majority of adults now own multiple mobile devices, reflecting the explosion in device ownership (Statista, 2016). Smartphone usage in our society motivates the researchers

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to discover new opportunities in various fields, specifically in education (Arain et al., 2019). The largest demographic of mobile device users is 18–29 years old which is also the typical age of college students. Almost all higher vocational colleges students have smart phones. Some students also bring other mobile devices such as IPAD to school. This provides technical support and basic conditions for mobile learning. Research also found that mobile learning can improve the experience (Biloš et al., 2017) and efficiency (Smith et al., 2021) of vocational skills training. Mobile learning gets rid of the limitations of traditional learning space and resources. Students can learn without being in a specific place or using specific teaching materials. This new learning method provides learning resources and learning ways for people's lifelong learning. More and more people accept M-learning. They are experiencing this non-traditional way of learning in different ways. The concept of mobile learning is being concerned and widely used.

2.1.1 Definitions of Mobile Learning

There is no unified definition of mobile learning. The history of m-learning dates back to early 1950, when academic researchers began to explore the relationship between E-learning and university. Truls Fagerberg et al. of NKI distance Education in Norway analyzed the concept of mobile learning in 2001. Learning is an activity that involves changes in an individual's perception, emotional attitude, cognitive abilities, or physical capacity. As a result, learning cannot be electronic or mobile. Of course, learning cannot be done in an electronic format, but learning resources and tools can be. Scholars have varying approaches to defining mobile learning, with some placing emphasis on its observable characteristics, others on the technological tools and devices involved, and still others on the dynamic interplay between teaching and learning. The concepts of digital learning and distance learning come from practice and have been accepted as an academic term generally. Distance education evolved from pen-and-paper correspondence courses to analog audio (radio, cassette) and video (television, videotape, videoconferencing) teaching techniques, and finally to personal computers. This evolution parallels the evolution of society from the industrial age to the information or electronic age. From the perspective of distance education, Dr. Keegan divides distance learning into three stages according to the different forms of learning: distance

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learning, E-learning and mobile learning, and optimistically believes that these three forms of learning are forming today's distance learning university, network university and mobile university in the future.

Before defining mobile learning, we need to identify these three similar concepts: Digital learning, E-learning and M-learning. Basak et al. (2018) suggested that E-learning is the learning supported by digital electronic tools and media and m-learning is the E-learning using mobile devices and wireless transmission. Finally Digital learning is any type of learning that is facilitated by technology. While having significant impact on the sustainable development and on the living conditions, the three concepts seem to be very closely related. But there are some differences among them. Their relationship can describe like this. M-learning is the subset of E-learning; D-learning is the combination of e-learning and m-learning (Basak et al., 2018). It is presented in figure 2.1.

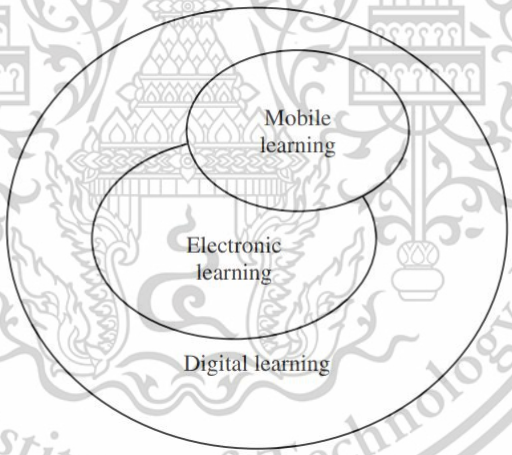

Figure 2.1 Relationship of D-learning, E-learning and M-learning

Source: Basak et al. (2018)

At present, there are three different cognitive orientations in the understanding of mobile learning, and the these differences often lead to different research focuses.

First, it is the mobile technologies that separates mobile learning from learning's other forms. If learning occurs through or with mobile device that is away from general learning surroundings of a person, it is mobile learning (O'Malley et al, 2003). This predominates over the literature. Mobile learning is defined by Desmond Keegan as the provision of training and

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education on smartphones, mobile phones and PDAs/palmtops. One of mobile learning's features is that it uses devices which citizens are used to carrying everywhere, which they regard as personal and friendly devices, which are cheap and easy to use, which they use constantly in life's all walks and in a variety of varying settings, apart from education (Keegan, 2002). Althunibat et al. (2022) define M-learning as the use of mobile devices in the teaching and learning process, as it focuses on using the techniques available in wireless communication devices to communicate information outside the classroom. It should be possible to utilize gadgets and devices. We can see more definitions in the following table.

Second, some researchers define mobile learning in terms of cognition. That is mobile learning is understood as a extended form of distance learning. This way is represented by Desmond Keegan, and it is mainstream in China. Distance education expert Desmond Keegan (2010) divides distance learning into three stages according to learning's different forms: distance learning, e-learning and mobile learning, and be optimistic that the three forms of learning are forming distance learning university, network university and the future of mobile university. Mobile learning is considered an extension of E-learning, which has the same learning content as e-learning, apart from the fact that knowledge and information are acquired through devices and mobile communication networks. Mobile learning research in China mainly takes network education as the platform, realizes the optimization and integration of the original digital learning resources with the help of transmission technology, and tries to transplant it directly to mobile devices. For example, various researches and practices are carried out on the platform of mobile learning system of School of Network Education in Shanghai Jiaotong University.

Third, Some researchers think of mobility from the perspective of learners rather than technology. A strong linage of research into conceptualizing mobile learning is traceable by reviewing the combined works of Sharples, Taylor, O'Malley and their colleagues. In their early research, According to Sharples et al. (2007), the idea of mobile learning was closely related to the device and had the ability to support lifelong learning. However, it soon became clear that rather than the device, the focus should be on the mobility of the learner. This led to considering mobile learning from the learner's perspective. More scholars accept this view and give more precise definitions such as Al-Adwan et al. (2018).

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Table 2.1 Summary of the Definitions

Perspectives	Authors	Definitions
Technology	Desmond Keegan (2002)	The provision of education and training on PDAs/palmtops/handhelds, smartphones and mobile phones
	Adejo et al. (2018)	A learning technique in which objects and materials essential for learning are supplied utilizing mobile devices, allowing anybody to access them from anywhere.
	Almaiah & Alismaiel (2019)	Education through the Internet/networks using personal mobile devices (m-devices), such as tablets and smartphones, to receive learning materials.
	Althunibat et al. (2022)	The use of mobile devices in the teaching and learning process, as it focuses on using the techniques available in wireless communication devices to communicate information outside the classroom.
Cognition	Desmond Keegan (2010)	Divide distance learning into three stages according to different forms of learning: distance learning, e-learning and mobile learning
	Kumar and Chand (2019)	Mobile learning is an extension of e-learning that allows users to accomplish learning using small and portable wireless devices.
Learner centered	O'Malley et al., (2003)	Any sort of learning that happens when the learner is not at a fixed, predetermined location, or learning that happens when the learner takes advantage of learning opportunities offered by mobile technologies
	Al-Adwan et al. (2018)	Mobile learning promotes learner-centred and personalized learning approaches by enabling students to interact and engage with educational processes away from

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Table 2.1 (continue)

Perspectives	Authors	Definitions
	Al-Adwan et al. (2018)	traditional learning places such as classrooms and desktop computers.
	Al-Emran et al. (2018)	The learning that is involved with the mobility of the learner where one can be engaged in the learning process without any restrictions to time and location.

2.1.2 Characteristics of Mobile Learning

As an emerging learning method, mobile learning has experienced rapid development in the era of mobile internet. It takes mobile terminals as carriers and utilizes modern information technology to bring learning resources and processes to learners anytime and anywhere. Mobile learning features like portability, personalization, and interaction providing learners with a new learning experience and approach. Following gives the main features from latest literature.

Portability: It is easy to carry such as PDA along with users in different locations, at home, office or even in a restroom (Almaiah et al., 2016). Portability provides users with access to a broader and greater flexible source of learning materials than what is offered in current classroom settings (Dias & Victor, 2022). Mobile devices are becoming increasingly lightweight while also offering more and more advanced functionalities. When compared to traditional PC clients and other digital devices, mobile devices are more portable and convenient for users to access. This trend has become particularly prevalent in recent years, with mobile devices becoming ubiquitous in our daily lives.

Interaction: It helps to interact with friends to send messages. It also helps to exchange data with other people and get and gain some extra knowledge. M-learning allows students to learn independently without the need for teachers, which increases their level of interaction with other users and information (Alghazi et al., 2021). On the one hand, there can be human-computer interaction between users and mobile learning platforms. Learners can share and exchange information anytime and anywhere on the platform, breaking the time and

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space restrictions. On the other hand, there is strong interaction between users. They can not only discuss problems and exchange learning experiences with each other, but also establish social relations and gain friendship through social interaction.

Sensitivity: Mobile devices can be used to find and gather real or simulated data (Al-Emran et al., 2018). It helps to gather data (real data and simulated data) unique to the current location, time, and the environment.

Connectivity: Connectivity relates to how the device connects to a network or other tools for operating applications (Sophonhiranrak, 2021). It presents the ability to learn through mobile technology by communicating with several devices in several different places(Alghazi et al., 2021). It helps to get a strong network where a learner can connect to mobile phones, data collection devices, and to a common network. Mobile learning applications can be used to access a variety of information and learning activities anytime and any-where with instant connectivity facility between students and instructors (Almaiah, 2018). The mobile devices have the capacity to connect student and instructor and create more constructive reflection. With a device, the classroom is always at the students and teachers fingertips with thousands of educational apps available to download(Dias & Victor, 2022).

Mobility: It refers to learning while on the move(Saroia & Gao, 2019). It allows for learning anywhere and anytime without having to come the university (Almaiah et al., 2021). Mobile devices enable students to control their individual learning and allow them to switch learning contexts conveniently from formal to informal or personal to social (Dias & Victor, 2022).

Personalization: It is very unique because it can help learners to customize learning information. There is evidence that mobile devices have encouraged independent learning making it easy for teachers to differentiate individual student needs (Dias & Victor, 2022). University students have varying demands when it comes to learning, and traditional digital learning methods may not meet the needs of every student. In mobile learning, learners can customize their learning content according to their individual needs (Gumbheer et al., 2022). This provides a more personalized learning experience and better addresses the diverse needs of university students.

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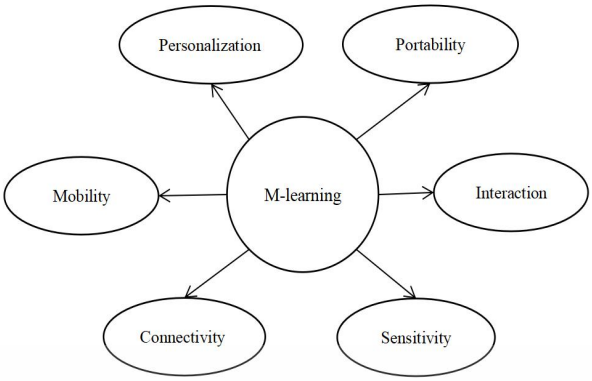

Figure 2.2 the Characteristics of Mobile Learning

2.1.3 Mobile Learning in China

In 2000, Desmond Keegan, an international distance educator, made an academic report "Distance Learning -- Digital Learning -- mobile Learning" at the 40th anniversary celebration of Shanghai TV University. The report introduces the concept of mobile learning to China for the first time and says that mobile learning represents the "future of learning". Since mobile learning entered China, it has experienced two stages of development: the initial exploration stage(2000-2010) and the rapid development stage (2010-2022).

The Initial Exploration Stage (2000-2010): At the beginning of the initial exploration stage, there is no concept of smart phone, and the device used does not have an operating system. Mobile phone SMS and WAP are the main learning methods of mobile learning. The browsing speed in this way is relatively slow, and the amount of information obtained is less, which cannot form a certain scale of users. With the rise of smart phones after 2006 and the emergence of Symbian (Nokia), Windows Mobile (Microsoft) and other operating systems, users' demand for mobile application software was generated. Therefore, in order to meet the market demand, some enterprises began to develop mobile learning apps, such as Mobile English Pass. After 2008, Android and IOS devices began to appear, and mobile learning began to develop. At this stage, researchers in China are conducting corresponding studies. Based on the researches worldwide, they try to explore the definition and theoretical basis of mobile learning. Ye & Xu (2004) proposed the basic concept of mobile learning and pointed out that mobile learning, as a new way of learning, is of great significance to the realization of

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lifelong learning. Yu (2007) systematically sorted out the development process of the three generations of mobile learning of "knowledge transfer, cognitive construction-situational cognition", which laid a solid theoretical foundation for subsequent studies. Combining literature analysis and application case study, Fu & Yang (2009) summarize the theoretical research and practice of mobile learning in China in the past ten years.

The Rapid Development Stage (2010-2022): With the rapid popularity of Android and IOS, mobile learning has entered a period of rapid development, setting off a boom in the development of mobile learning apps. Enterprises are participating in the development of mobile learning apps one after another, and a large number of mobile learning apps are widely distributed in primary and secondary education, higher education and other fields. Scholars began to pay attention to the development of mobile learning platform and the design of learning resources. Yan (2016) developed mobile courses based on WeChat platform to open the application of practical teaching. With mobile MOOC platform as the background, Xiao et al. (2017) designed a "micro-classroom" mobile learning system based on activity theory and user portrait theory. Li & Xu (2018) applied mobile learning to higher education and proposed a new teaching model of "mobile learning plus smart classroom" with interactive concept as the core. Wang & Feng (2019) believe that the picture of mobile learning resources is an important factor affecting learners' experiences, and they optimize the picture design from the sensory layer, behavioral layer and emotional layer to improve the learning experience of users.

We searched the literature of "mobile learning, mobile education and m-learning" in the journal database of CNKI from 2010 to 2022, and a total of 17008 related literature were obtained. The annual literature quantity is plotted as follows. It can be seen that the number of published papers has been increasing, indicating that mobile learning has received extensive attention from scholars in China, and that the research value in the field of mobile learning is still to be explored. In the past three years, the number of published papers has declined, reflecting that the research has been relatively mature.

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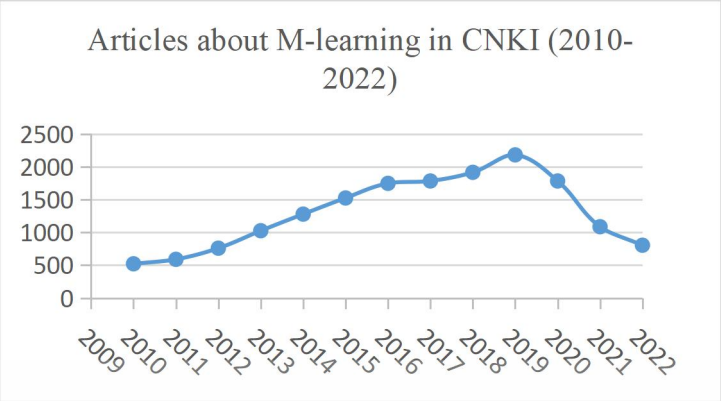

Figure 2.3 Articles about M-learning in CNKI (2010-2022)

Source: China national knowledge internet

2.1.4 Mobile Learning APPs in China

With the rapid development of mobile technology, the use of mobile terminal equipment is more and more popular, followed by the development of a large number of mobile applications (Alowayr, 2022; Islam, 2016). The advantages of mobile terminals are mainly reflected in the mobile terminals can install a variety of mobile applications. Mobile applications are referred to as mobile APPs, generally installed on a variety of mobile terminal devices, simple operation, but for people's work, study, life to provide a lot of convenient services (Kaur & Kaur, 2022). According to "2021 Mobile Internet Industry Development Report" issued by Talkingdata mobile data center, people increasingly rely on various applications closely related to life, especially in the fields of health care, education and reading. As a learning tool, mobile learning APP can provide users with services for learning activities anytime and anywhere, which has great educational value (Al-Adwan et, 2018)

By investigating the mainstream application market and referring to relevant survey reports of China Business Industry Research Institute (2022) and E-commerce Research Center (2022), we found that mobile learning apps are mainly divided into the following categories:

(a) Vocational Training APPs: Vocational Education APPs represented by China Public Education: carry out online training and guidance courses centering on the national post recruitment examination. The course content is highly targeted; Skills Learning APPs

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represented by the driving test can help candidates to master certain skills scientifically and effectively through a reasonable learning schedule.

(b) Language Learning APPs: Hundred Words Chopping with the functions of word query and sentence translation; Fluent English Speaking with the functions of word memory, listening practice, situational oral dialogue; English learning platforms supported by News and information, such as China Daily provide high-quality English news and consulting services.

(c) Question and Answer: Knowledge and Answer APPs represented by Zhihu concentrate professional authorities from various industries to provide high-quality answers to people effectively.

(d) Interest: Interest learning platform represented by Himalaya FM gathers a large number of cultural celebrities and we-media persons, covering finance, music, news and business, which is very helpful for people to use fragmented time for learning.

(e) K12 Education: K12 education platform represented by Homework Help provides auxiliary functions such as shooting graphic problems to cultivate children's independent learning ability.

(f) Comprehensive APPs: Learning Power is not only based on Party news, but also provides massive free learning resources for the whole society. Online learning platforms represented by NetEase Open Course provide free teaching video resources for students, featuring strong professionals.

We collect most useful APPs in the six categories with their main functions and features as following table.

Table 2.2 Different APP categories

APP category	Representatives	Functions	Features
Vocational Training	China Public Education, Fenbi, driving test	Vocational training; Master skills	Strong pertinence; Focus on practical knowledge

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Table 2.2 (continue)

APP category	Representatives	Functions	Features
Language Learning	Hundred Words Chopping, Youdao Dictionary, Fluent English Speaking, China Daily, BBC News, Mint Reading	Language learning AIDS; Help improve listening, speaking and reading in a certain field	Contextualization of language learning; Easy to generate achievement
Question and Answer	Zhihu, Baidu Knows, Wukong Questions	Answer questions quickly and provide effective help	Discussion of hot issues; Provide quality PGC content
Interest	Himalaya FM, Dragonfly FM, the Lazy listen to books, Wechat Reading	Read a book; Listen to the book/class	Fragmented learning; Leisure time
K12 Education	Homework Help, Ape Tutoring, VIPKID, Dada English	Shoot graphic problem; Help homework; Exam-oriented learning	Massive question ; Intelligent operation; Cultivate independent learning.
Comprehensive APPs	Learning Power, NetEase Open Course and China University MOOC	Provide online teaching resources	Rich in content; Professional; Provide credit system for students; free

2.1.5 Mobile Learning in Higher Vocational Colleges

In contrast to academic higher education, higher vocational colleges in China is offered a shorter period of study and focuses on developing practical job skills to prepare students for the workforce (Li et al., 2022). What is more, Chinese students in higher vocational colleges are of a lower socioeconomic status than students in academic HEIs (Abrassart & Wolter, 2020), and these two groups differ in learning habits, motivation and ability. They have less self-control and find it difficult to study efficiently and intensively in the classroom for long periods. To some extent, they are tired of teachers teaching from the book in class. They are in the age of natural liveliness and love new things, so they prefer new learning resources that are illustrated, audio-visual and can keep up with the development trend of The Times. Only

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such learning materials can capture their curiosity and interest points, and they prefer interactive classes where they can express themselves and communicate with classmates

A teacher's choice of learning media in a vocational high school environment must be able to fit students' learning demands while also meeting the output objectives. The emergence of mobile learning can just meet the personalized learning needs of higher vocational students. Through mobile learning, they can learn at any time and anywhere according to their own needs, and freely choose a variety of teaching resources, including class playback, national high-quality open courses, to supplement the teaching knowledge that cannot be covered in traditional classes. Mobile learning enables teachers to create dynamic and captivating courses by integrating audio, video, text, and images. Teachers can assign real-time tasks for students to use mobile devices for online research or do a quiz. M-learning makes the education process more acceptable to students, especially among the younger generation who are more likely to pursue and use new technology (Alghazi et al., 2021). Mobile learning can help students be more active in their process of discovery, be more mobile in the educational process, and have more timely and faster interactions, all of which help them be more motivated and learn more.

2.1.6 Technology Acceptance Models towards Mobile Learning

Literature review reveals a number of different models which have been used for explaining technology adoption and application in individuals (Qashou, 2021; Shaya et al., 2023). Many researchers have employed different technology acceptance models. Among them the most popular used models is the TAM, and the UTAUT, which was introduced by Venkatesh et al. in 2003.

Technology acceptance model (TAM) has been regarded as first theoretical model to explain psychological factors to capture individuals' attitude. TAM refers to the impact of external variables on internal beliefs and proposes a series of sequential relationships of beliefs, attitudes, and behavioral intentions that ultimately lead to actual use of the system and help predict user acceptance of information systems and technologies (Almaiah & Alismaiel, 2018). TAM mainly includes six research variables: Perceived Usefulness, Perceived Ease of Use, Attitude toward using, Behavioral Intention to Use, Actual System Use and external

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variables (shown in Figure 2.4). Two main determinants are: (1) Perceived usefulness, reflecting the extent to which a person believes that using a specific system improves his work performance; (2) Perceived ease of use, which reflects the degree to which a person thinks it is easy to use a specific system. In fact, TAM is derived from a well-known model of Theory of Reasoned Action (TRA). TAM derives its theoretical roots from a rich literature in social psychology where actual behavior, intentions to perform the behavior, attitude as a determinant of intentions, and the antecedents of attitude, have been examined both theoretically and empirically for several decades (Fishbein 1967; Ajzen & Fishbein 1973).

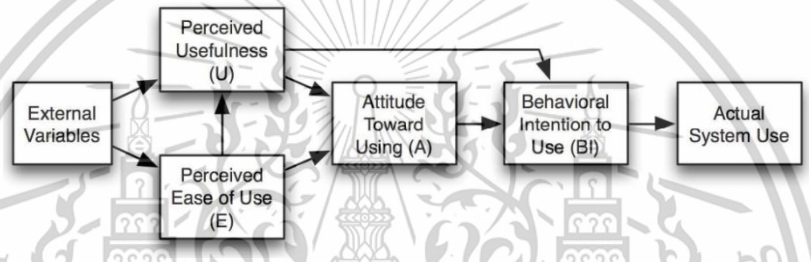

Figure 2.4 TAM Model

Source: Davis (1989)

Many researchers have engaged in exploring the most influential factors for the use of mobile learning by TAM. Aburub & Alnawas (2019) employed the TAM model to explore the acceptance of mobile learning in Jordan. The findings implied that cognitive satisfaction and ease of use were the main factors to predict students' acceptance of mobile learning. However, factors such as personal integrative gratification, hedonic gratification, and perceived usefulness were not important. Almaiah & Alismaiel (2019) utilized a integrated model which combines TAM and the updated DL & ML model to investigate the impacts of three quality factors on the acceptance of mobile learning applications. They claimed that the system quality, content quality, and service quality had a considerable impact on motivating students to adopt and utilize mobile learning applications.

However, some scholars (Tsai et al., 2018) have claimed that the TAM has several shortcomings, including

(1) There is insufficient insight into the individual's views on the new system;

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(2) Ignore their indicators and directly investigate the external variables of perceived ease of use (PEOU) and perceived usefulness (PU);

(3) Ignoring the relationship between use attitude and use intention;

In order to make TAM more realizable, scholars have extended TAM. Venkatesh & Davis proposed TAM2 in 2000. Most of the influencing factors in TAM2 come from TAM. The improvement is that the attitude variable in the original model is removed and five new variables are introduced, as shown in the figure. Two moderating variables have also been added: Experience, Voluntariness.

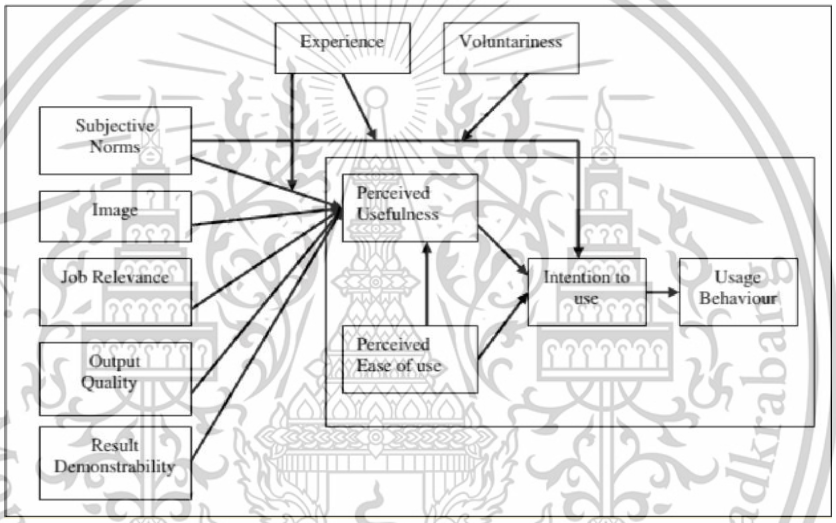

Figure 2.5 TAM2 Model

Source: Venkatesh & Davis (2000)

Little researches have been done by TAM2 regarding to mobile learning. Although Davis's (1989) TAM Model has been applied to various studies on technology adoption in a number of different contexts, ranging from consumers' perspective to organizational perspective. Yet scholars have introduced more robust theories which tenaciously focus on organizational perspective and consumers' perspective. Venkatesh et al. (2003) proposed the unified theory of acceptance and use of technology (UTAUT) focusing on technology adoption behaviour in organizations.

2.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

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To examine a person's behavior intention and use behavior, many models like TRA, TAM, or UTAUT models could be used. Each model has its advantages and disadvantages: TAM is a tool that is used to explore technology adoption in a variety of contexts, but no more than 40% of the variance in the dependent variable can be explained, which leaves room for additional antecedents of acceptance (Ma et al., 2019). Moreover, TAM has more limitations and is frequently redefined resulting in theoretical chaos and confusion. Literature review revealed that UTAUT has become one of the most embraced and widely used models for testing the adaptation of ICTs in various fields, such as online learning, internet banking, e-service, health and e-governance (Almaiah et al, 2022). The UTAUT model synthesises significant factors of previously established theories such as TAM, TRA, TPB, IDT etc. Venkatesh et al. (2003) confirmed UTAUT's significant improvement in explaining IT usage behavior and encouraged other scholars to validate and test the model using different techniques, contexts, users, and moderators. UTAUT is applicable in the context of m-learning (Al-Adwan et al., 2018). In mobile learning, students need to use mobile learning system to realize learning activities, which indicates that mobile learning system is a kind of information technology. Thus UTAUT can be a useful tool to explore the implementation of mobile learning. Moreover, researchers found that UTAUT has the upper explanatory power compared to other models and theories in IS/IT acceptance context (Almaiah et al, 2019). In a review study by Walldén et al. (2016), 69 published studies were reviewed and concluded that the UTAUT is a valid and robust model based on substantial empirical evidence in the studies. Besides, the UTAUT model is applicable in mandatory settings (Venkatesh et al. 2003). Higher Vocational colleges now have many courses using hybrid learning method, part of the class is completed in classroom, part of the class is completed on the mobile platform, by the teacher to choose the appropriate platform. Therefore, students in some colleges now are forced to use mobile learning platforms to some degree. Due to the applicability to the context of the m-leaning and upper explanatory power, this study selects UTAUT to develop a conceptual model in order to achieve a solid base to explain why students accept and use mobile learning.

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Venkatesh et al. (2003) compared these eight models by an empirical study, and based on the results, they proposed the UTAUT. The results showed that the UTAUT explained 70% of the variance in IT usage behaviour and is better off than any of the eight individual model. The eight models consist of the theory of reasoned action (TRA) (Fishbein & Ajzen, 1973), the technology acceptance model (TAM) (Davis, 1989), the motivational model (MM) (Davis, Bagozzi & Warshaw, 1992), the theory of planned behaviour (TPB) (Ajzen, 1991), the combined TAM and TPB (C-TAM-TPB), the model of PC utilisation (MPCU), the innovation diffusion theory (IDT) and the social cognitive theory (SCT) (Bandura, 1986; Compeau & Higgins, 1995). UTAUT contains four core determinants of IT use behaviour, and up to four moderators of key relationships (see Figure 2.6). UTAUT points that performance expectancy, effort expectancy, social influence and facilitating conditions are determinants of behavioral intention or use behaviour, and that gender, age, experience and voluntariness of use have moderating effects in the acceptance of innovation.

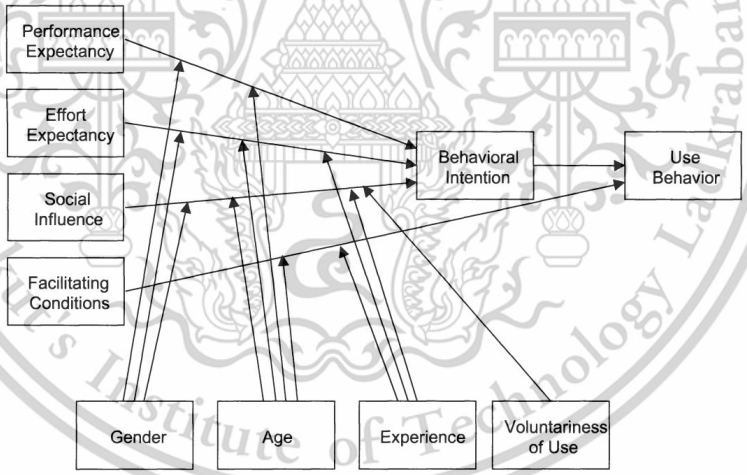

Figure 2.6 UTAUT Model

Source: Venkatesh et al. (2003)

One research has been carried out by Landutfi et al. (2022) to propose an integrated model of UTAUT combined with the DeLone McLean model. The aim is to examine the influence on the intentions and satisfaction of users toward mobile learning use in the context of Saudi learning institutions. By using an online questionnaire, the study obtained mobile learning user data. On one hand, the influence of performance and effort expectancy, and FC

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on intention toward m-learning use was supported by the findings. However, the significant influence of SI was not supported by the findings. Moreover, system, intention, and user satisfaction were found to positively and significantly influence mobile learning usage.

UTAUT model has been used by Abbad (2021) to study students' intention to use and their use behavior of an e-learning system called Moodle. They collected data from 370 undergraduate students. The results indicated that PE and EE affected behavioral intention to use Moodle whereas SI did not. Moreover, the results supported the direct impact of behavioral intention and FC on students' use of Moodle.

Alharbi et al. (2017) utilized UTAUT to analyze the factors that affect university instructors' intentions to use mobile learning. Data was collected online from Eighty instructors. According to the results, performance experience, effort expectancy, social influence, and facilitating conditions altogether predicted the instructors' use of mobile learning, as 67% of the variation was found to be affected by these variables in the multiple regression analysis outcome. Moreover, the results also indicated that the best predictor of instructors' behavioral intentions to use mobile learning was effort expectancy.

Bervell & Umar (2017) applied the UTAUT model as well as the Partial Least Squares approach to examine a combined linear and non-linear relationships based UTAUT model. They used the questionnaire to obtain the data. The sample consist of 267 respondents (tutors) from a distance-based higher education milieu with a countrywide distribution. Results indicated that PE, EE and FC were all positively related to behavioral intention (BI). According to the results, the strongest predictor of BI was effort expectancy with a relatively higher beta value, followed by facilitating conditions. Results obtained also showed that there exists non-linear relationships between exogenous factors to better explain constructs' behaviour in the model. A new relationship between social influence and facilitating condition was also discovered. The study thus suggested that there is the need to include non-linear relationships in the UTAUT model to augment the predictive effects and explanations of the constructs' relationships in technology acceptance research. It further recommended a comparative analysis between a proposed comprehensive UTAUT model with non-linear relationships and moderators to the original UTAUT model for further empirical analysis.

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The factors that promote the actual use of the mobile-LMS by students that take online learning programs has been studied by Ikhsan et al. (2021). The data contained 500 students as the target sample, and the students were filtered based on using the mobile-LMS for at least two semesters. Multivariate SEM-PLS analysis was used by the study to answer the research hypothesis, and the factors examined employed the concept of UTAUT. Subsequently, the results indicated that performance and effort expectancy, social influence, and facilitating conditions positively and significantly affect behavioral intention. Positively and significantly Facilitating conditions and behavioral intention also influence the actual use of the Mobile-LMS. Consequently, the UTAUT concept displays a motivating factor for students to continuously use the Mobile-LMS in online learning.

2.2.1 Use Behavior

Behavior is a socially formed attitude of people, involving the outcome of sensitive activities, values towards positions, issues, people or events. According to Davis (1989), intention to use new technology has a major role in its actual usage, and based on TAM, behavioral intention to use is the top determinant of actual system use.

Table 2.3 Definition of Use Behavior

Scholars/Researchers	**Definition**
Maillet et al. (2015)	The evaluation of the use of the technology to support decision making and work integration.
Yeop et al. (2019)	Action in using or implementing a learning technology
Wang & Xing (2019)	Student self-reported actual usage of digital textbook
Nikolopoulou et al. (2020)	the extent to which students use their mobile phones in their studies as learning tools
Al-Rahmi et al. (2020)	the degree based on the duration of use of certain technologies to which individuals use the functions of information systems.
Bin et al. (2020)	the teachers' opinions of how often they use ICT for their teaching and research purposes

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Table 2.3 presented researchers' definitions of Use behavior. This study has concluded that use behavior implies the degree of usage of mobile learning in terms of frequency and duration.

Botero et al. (2018) adapted and expanded the UTAUT model to evaluate the dimensions that affect behavioral intention and the practical use of Mobile Assisted Language Learning (MALL). Collect and analyze data using structural equation models. The results indicate that social influence and convenience conditions affect the willingness to use MALL; performance expectations, social influence, and convenience conditions can also affect students' attitudes towards using MALL. The model also indicates that behavioral intention has an impact on the use of MALL. The conclusion drawn from the study is that higher education students in developing countries such as Colombia have a positive attitude towards MALL. However, in order for MALL to successfully integrate into education, it is necessary to improve the convenience conditions and play a more influential role in the education industry.

Table 2.4 Literature review on Use Behavior

Scholars/Researchers	**Latent Variable**	**Observed Variables**	**Industry**
Alyoussef (2021)	Use Behavior	1) Use frequencies 2) Recommendation	Education (M-learning)
Bin et al. (2020)	Use Behavior	1) Teaching purpose, 2) Research purpose 3) Academic purpose	Education (ICT)
Abbad (2021)	Use Behavior	1) Preference 2) Regular user	Education (MOOCs)
Islam (2016)	Use Behavior	1) Teaching purpose, 2) Research purpose 3) Academic purpose	Education (ICT facilities)
Almaiah & Alismaiel (2019)	Use Behavior	1) Frequently use 2) Frequently use in the future	Education (M-learning)

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Table 2.4 presents a summary of the literature on the use behavior. The observed variables of use behavior include 1) Preference, 2) Frequently use, 3) Recommendation. Each observed variable contains different items as follows.

Table 2.5 Items of Use Behavior

Observed Variables	Items	References
Preference	**UB1:** I prefer to use M-learning when available.	Abbad (2021); Almaiah, Alamri & Al-Rahmi (2019)
	UB2: I aim to use M-learning instead of traditional ones.	Abbad (2021); Al-Adwan, Al-Adwan & Berger (2018)
Frequently use	**UB3:** I use M-learning daily.	Alyoussef (2021); Almaiah & Alismaiel (2019); Mohammadi (2015)
	UB4: I use M-learning sometimes.	Almaiah & Alismaiel (2019); Altalhi (2021); Mohammadi (2015)
	UB5: I will use M-learning daily in the future.	Almaiah & Alismaiel (2019); Al-Adwan, Al-Adwan & Berger (2018)
Recommendation	**UB6:** I recommend M-learning for others to use.	Alyoussef (2021)

Alyoussef (2021) developed a new model and conducted confirmatory factor analysis (CFA) to better understand how students use mobile learning in higher education. This study is theoretically based on the UTAUT and the TAM. In theory, factors related to the adoption of mobile learning in higher education have been analyzed, which are believed to contribute to perceived ease of use, perceived usefulness, attitudes towards mobile learning, and use behavior of mobile learning. A questionnaire survey was conducted on 362 randomly selected college students. Perceived convenience conditions, PE, EE, SI, and perceived enjoyment

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have a significant positive impact on PEOU and PU, while PE have a negative impact on PEOU. They suggest that instructors encourage students to use mobile learning for educational purposes in higher education.

Based on the literature, theories, concepts, and researchers' findings of the use behavior, the latent variable use behavior is comprised of three observed variables, as shown in figure .

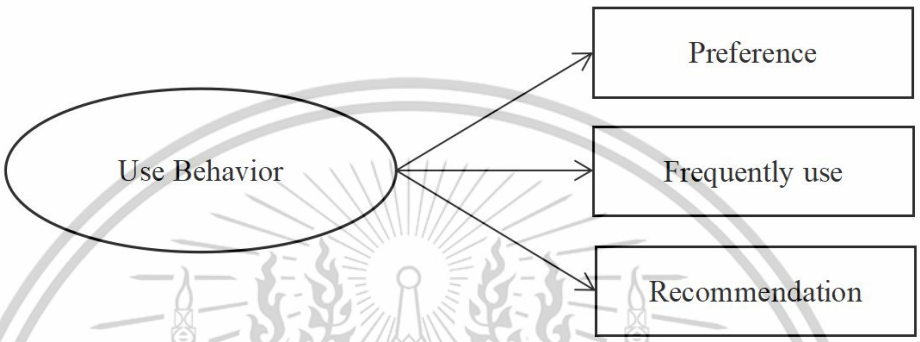

Figure 2.7 Model for Use Behavior

Source: Alyoussef (2021) & Abbad (2021)

2.2.2 Behavioral Intention

The term "behavior intention" was first put forward by Fishbein and is one of the core indicators to predict the occurrence of behavior. In 1973, Fishbein & Ajzen operationalized behavioral intention into the possibility of individual action, believing that behavioral intention is people's expectation of their own behavior in a given environment. According to Davis (1989), intention to use new technology has a major role in its actual usage, and behavioral intention to use is the top determinant of actual system use. Behavioral intention is a significant determinant behind the actual use of technology in different intention models (Venkatesh et al. 2003, 2012).

Table 2.6 Definition of Behavioral Intention

Researchers	**Definition**
Ajzen & Fishbein (1973)	People's expectation of their own behavior in a given environment

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Table 2.6 (continue)

Researchers	**Definition**
Davis (1989)	The behavioral readiness to accept, use or adopt a particular technology
DeLone & McLean (2003)	An emotional and psychological entity that provides a description of the user's beliefs and a mind state that is formed by their experience
Yeop et al. (2019)	The level of desire for doing or remitting an action in using or implementing a learning technology
Alshehri et al. (2019)	The probability that individuals will perform the behavior.
Kumar & Bervell (2019)	Degree to which a student purposefully formulates an execution plan towards performing instructional activities in Google Classroom
Nikolopoulou et al. (2020)	The extent to which students intend (and continue) to use mobile phones in their studies
Shaya, Madani & Mohebi (2023)	A person's likelihood of engaging in a particular behavior

Table 2.6 presented researchers' definitions of behavioral intention. This study has concluded that behavioral intention implies the readiness or willingness of a student to take action to use the M-learning.

Nikolopoulou et al. (2020) used the UTAUT2 model to evaluate college students' behavioral intentions to accept and use mobile phones in learning. Participants were 540 students from different universities in Greece who completed an online questionnaire. In their study, the most important predictors of students' behavioral intentions to use mobile phones were habit (the strongest one), performance expectancy, and hedonic motivation. The most important predictor of actual cell phone use is behavioral intention. Gender, age, and experience had no moderating effects. The results of this study strengthen the evidence for cell phone acceptance among college students and have implications for student training.

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Table 2.7 Literature review on Behavioral Intention

Scholars/Researchers	Latent Variable	Observed Variables	Industry
Venkatesh et al. (2003)	Behavior intention	1) Intention to use 2) Predicting to use 3) Planning to use	Different industries (Entertainment, banking, et al.)
Thomas et al. (2013); Almaiah et al. (2019); Fagan (2019)	Behavior intention	1) Intention to use 2) Predicting to use	Education (M-Learning)
Al-Adwan, Al-Madadha & Zvirzdinaite (2018)	Behavior intention	1) Intention to use 2) Predicting to use 3) Planning to use	Education (M-Learning)
Tseng et al.(2019)	Behavior intention	1) Intention to use 2) Predicting to use 3) Planning to use	Education (MOOCs)
Meet et al. (2022)	Behavior intention	1) Intention to use 2) Planning to use	Education (MOOCs)
Li et al. (2023); Shaya, Madani & Mohebi (2023)	Behavior intention	1) Intention to use 2) Predicting to use 3) Planning to use	Education (M-Learning)

Table 2.7 presents a summary of the literature on the behavioral intention. The observed variables of behavioral intention to use include 1) intention to use , 2) prediction to use , 3) planning to use. Each observed variables contains different items as follows.

Table 2.8 Items of Behavioral Intention

Observed Variables	Items	References
Intention to use	**BI1:** I intend to use M-learning in the future.	Venkatesh et al. (2003); Tseng et al., (2019); Meet et al. (2022); Li et al. (2023)

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Table 2.8 (continue)

Observed Variables	Items	References
Predicting to use	**BI2:** I predict I would use M-learning in the future.	Venkatesh et al. (2003); Tseng et al., (2019); Meet et al. (2022); Li et al. (2023)
Planning to use	**BI3:** I plan to use M-learning in the future.	Venkatesh et al. (2003); Tseng et al., (2019); Meet et al. (2022); Li et al. (2023)

Tseng et al. (2019) investigated the influencing factors of teachers' acceptance and use of MOOCs based on UTAUT2 model. The researchers used an online survey to collect the data from university teachers in Taiwan. Partial least squares structural equation model (PLS-SEM) was used for data analysis. The research results showed that performance expectations, social influence and convenience conditions promote teachers' behavioral intention to adopt MOOCs. Furthermore, facilitative conditions and behavioral intentions determine teachers' adoption of MOOCs. However, effort expectations and hedonic motivations did not drive teachers to adopt MOOCs. On this basis, several important theoretical and practical implications are discussed.

Based on the literature, theories, concepts, and researchers' findings of the behavioral intention, the latent variable behavior intention is comprised of three observed variables, as shown in figure.

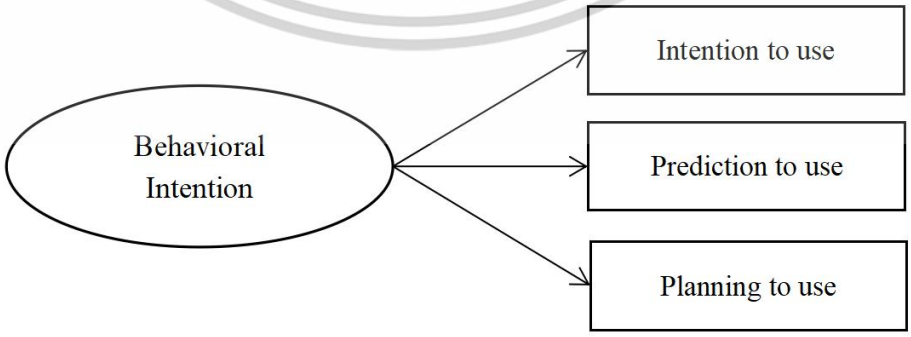

Figure 2.8 Model for Behavioral intention

Source: Venkatesh et al. (2003)

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2.2.3 Performance Expectancy

Performance Expectancy is a key construct that determines adoption and eventual usage of the relevant technology and has been justified as the strongest predictor of BI to use a technology (Venkatesh et al. 2003, 2012). Venkatesh et al. (2003) defined Performance Expectancy as the degree to which a person believes that using technology can assist him or her succeed in their job performance, is comparable to perceived usefulness in TAM. Venkatesh et al. (2012) defined Performance Expectancy as the belief of the user that targeted technology will improve his or her performance to obtain job-related gains. Five constructs from existing models have been used to form performance expectancy: perceived usefulness (TAM/TAM2 and C-TAM-TPB (combined TAM and the Theory of Planned Behaviour-TPB)), job-fit (The Model of Personal Computer Utilization), extrinsic motivation (the Motivational Model), outcome expectation (the Social Cognitive Theory) and relative advantage (Innovation Diffusion Theory) (Venkatesh et al., 2003). In terms of performance expectancy, It is recommended that students regard mobile learning as beneficial because it allows them to quickly get information at a convenient time and place and use the device of their choice.

Table 2.9 Definition of Performance Expectancy

Scholars/Researchers	**Definition**
Venkatesh et al. (2003)	Degree to which a person believes that using technology can assist him or her succeed in their job performance
Rosen (2004); Yee & Abdullah (2021)	The perception of job advantages obtained via the use of the system
Venkatesh et al. (2012); Jalil, Rajakumar & Zaremohzzabieh (2022)	The belief of the user that targeted technology will improve his or her performance to obtain job-related gains.
Lwoga and Komba (2015)	How certain the students are that the system will help them do better in their classes
Kaliisa, Palmer & Miller (2017)	The degree to which an individual believes the technology will lead to better rewards or outcomes in a given task.

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Table 2.9 (continue)

Scholars/Researchers	Definition
Gunasinghe et al. (2020)	Academician's assumption that technology will help them do their job tasks more effectively and efficiently.
Alghazi et al. (2021)	The degree to which a student thinks that using mobile learning will increase their ability to gain knowledge

Table 2.9 presented researchers' definitions of performance expectancy. In this study, performance expectancy is defined as the degree to which an individual believes that use of m-learning will provide advantages and enhance their performances for educational activities.

Gunasinghe et al. (2020) employed the UTAUT-3 model to investigate the adoption of e-learning by academicians. Data were collected using a self-administered questionnaire sent to target respondents via Google Forms using simple random sampling with a 7-point Likert scale. 441 academicians were consider to be the respondents for this survey. Data analysis used structured equation modeling. The results showed that performance expectations, effort expectations, and hedonic motivations are important factors that influence academicians' adoption of e-learning, which demonstrated the significance of the factor of PE.

Table 2.10 Literature review on Performance Expectancy

Scholars/Researchers	Latent Variable	Observed Variables	Industry
Venkatesh et al. (2003)	Performance Expectancy	1) Perceived usefulness 2) Relative advantage 3) Outcome expectation	Different industries (Entertainment, banking, et al.)
Venkatesh et al. (2012)	Performance Expectancy	1) Perceived usefulness **2)** Relative advantage	mobile Internet technology
Al-Adwan, Al-Adwan & Berger (2018)	Performance Expectancy	1) Perceived usefulness 2) Relative advantage 3) Outcome expectation	Education (M-Learning)

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Table 2.10 (Continue)

Scholars/Researchers	Latent Variable	Observed Variables	Industry
Tseng et al., (2019)	Performance Expectancy	1) Perceived usefulness 2) Relative advantage 3) Outcome expectation	Education (MOOCs)
Alghazi et al. (2021)	Performance Expectancy	1) Perceived usefulness 2) Relative advantage 3) Outcome expectation	Education (M-Learning)
Meet et al. (2022)	Performance Expectancy	1) Perceived usefulness 2) Relative advantage	Education (MOOCs)
Li et al. (2023)	Performance Expectancy	1) Perceived usefulness 2) Relative advantage 3) Outcome expectation	Education (M-Learning)

Table 2.10 presents the literature, theories, and concept of the performance expectancy. From the literature the performance expectancy have 3 observed variables, which are1) perceived usefulness, 2) relative advantage, and 3) outcome expectation. Each observed variable contains different items as follows.

Table 2.11 Items of Performance Expectancy

Observed Variables	Items	References
Perceived Usefulness	**PE1:** I would find M-learning useful in my learning.	Abbad (2021); Venkatesh et al. (2003); Meet et al. (2022); Alghazi et al. (2022)
	PE2: Using M-learning would make it easier for my learning.	Venkatesh et al. (2003);

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Table 2.11 (continue)

Observed Variables	Items	References
Perceived Usefulness	**PE3:** Using M-learning would improve my learning performance.	Venkatesh et al. (2003); Shaya, Madani & Mohebi (2023); Sidik & Syafar (2020); Chao (2019)
	PE4: Using mobile learning would help me prepare before class and review after class.	Huang (2020)
Relative Advantage	**PE5:** Using the M-learning enables me to accomplish tasks more quickly.	Venkatesh et al. (2003); Meet et al. (2022); Alghazi et al. (2022)
	PE6: Using the M-learning increases my productivity.	Venkatesh et al. (2003); Shaya, Madani & Mohebi (2023); Meet et al. (2022); Altalhi (2021)
	PE7: Using M-learning system increases the quality of learning process.	Venkatesh et al. (2003); Li et al. (2023); Almaiah, Alamri & Al-Rahmi (2019)
Outcome Expectation	**PE8:** Using a M-learning platform increases my chances of learning things that are important to me.	Li et al. (2023); Shaya, Madani & Mohebi (2023); Meet et al. (2022); Chao (2019);
	PE9: If I use M-learning, my classmates will perceive me as competent.	Venkatesh et al. (2003);

Almaiah, Alamri & Al-Rahmi (2019) adopted the UTAUT model to examine the impact of different factors identified on the adoption of mobile learning applications in higher education. This research considered the four main factors of UTAUT model as part of the influencing factors. An online questionnaire was distributed to 697 college students. Data

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analysis was performed using scanning electron microscopy. The findings also showed that PE, EE, and accommodation conditions were predictors of usage intention, which demonstrated the significance of the factor of performance expectancy. The results of this study provide related information on how higher education institutions can improve students' acceptance of mobile learning systems to support the use of mobile technologies in learning and teaching processes.

From the literature, concepts, theories, and researchers conducted on the performance expectancy, the following model was obtained for the performance expectancy, which comprised three observed variables.

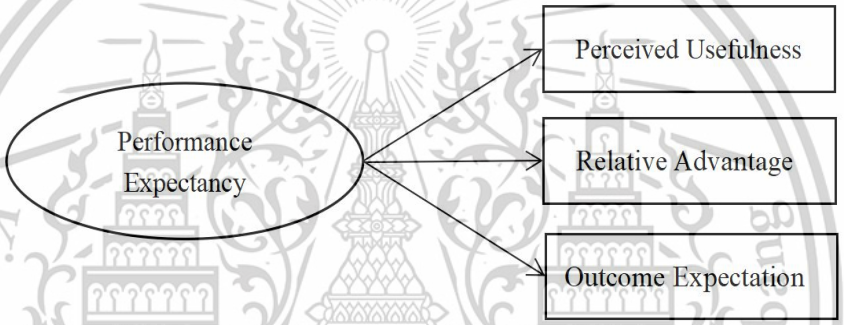

Figure 2.9 Model for Performance Expectancy

Source: Venkatesh et al. (2003)

2.2.4 Effort Expectancy

The degree of ease associated with the usage of a system is defined as effort expectancy (EE) by Venkatesh et al. (2003), which is comparable to perceived ease of use in TAM. Effort expectancy is defined as the "level of effort a consumer thinks a specific task will require" (Venkatesh et al., 2012). The easier the technology is to use, the more chances it has of being accepted.Venkatesh et al. (2003) employ three main constructs from various models to capture the concept of effort expectancy. These constructs include perceived ease of use (the Technology Acceptance Model-TAM, TAM2), ease of use (the Innovation Diffusion Theory) and complexity (the Model of PC Utilisation-MPCU).

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Table 2.12 Definition of Effort Expectancy

Scholars/Researchers	Definition
Venkatesh et al. (2003)	The degree of ease associated with the use of the system
Venkatesh et al. (2012)	The belief of an individual that his or her interaction with the targeted technology is trouble-free
Rosen (2014)	The perception of ease associated with using the system.
Lwoga & Komba (2015)	The degree to which students find it easy or difficult to accept and use e-learning systems
Gunasinghe et al. (2020)	Academicion's belief that technology platforms are easy to use
Yee & Abdullah (2021)	The level of comfort/effort associated with customers' use of technology
Nikolopoulou et al. (2022)	the level of expectation of students that the use of mobile phones will not be characterized by physical and mental efforts (ease of use of phones for their studies).
Shaya, Madani & Mohebi (2023)	the amount of ease that individuals expect to feel when using a computer system

Table 2.12 presented researchers' definitions of effort expectancy. In this study, effort expectancy is defined as the level of effort that the students is convinced they have to use mobile learning to complete the task.

Al-Rahmi et al. (2020) conducted UATUT to verify the performance of social media applications in new learning environments. This article aimed to shed light on the impact of social media use on behavioral intentions and actual use, as well as on teaching performance in higher education. Questionnaires were distributed to a total of 206 college students. The results show that each independent variable (PE, EE, FC, SI) has a direct impact through behavioral intention to use, while actual use achieves learning purposes through the use of social networks. This article confirmed the significance of effort expectancy.

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Table 2.13 Literature review on Effort Expectancy

Scholars/Researchers	Latent Variable	Observed Variables	Industry
Venkatesh et al. (2003)	Effort Expectancy	1) Perceived Ease of Use 2) Ease of Use	Different industries (Entertainment, banking, et al.)
Venkatesh et al. (2012)	Effort Expectancy	1) Perceived Ease of Use 2) Ease of Use	Mobile Internet
Tseng et al. (2019)	Effort Expectancy	1) Perceived Ease of Use 2) Ease of Use	Education (MOOCs)
Al-Adwan, Al-Adwan & Berger (2018)	Effort Expectancy	1) Perceived Ease of Use 2) Ease of Use	Education (M-Learning)
Thomas et al. (2013); Alghazi et al. (2021)	Effort Expectancy	1) Perceived Ease of Use 2) Ease of Use	Education (M-Learning)
Jalil et al. (2022)	Effort Expectancy	1) Perceived Ease of Use 2) Ease of Use	Education (IR 4.0 technology)
Li et al. (2023)	Effort Expectancy	1) Perceived Ease of Use 2) Ease of Use	Education (M-Learning)

Table 2.13 presents a summary of the literature on the effort expectancy. The observed variables of effort expectancy include 1) Perceived Ease of Use, 2) Ease of Use. Each of observed variables contains different items as follows.

Table 2.14 Items of Effort Expectancy

Observed Variables	Items	References
Perceived Ease of Use	**EE1:** My interaction with M-learning would be clear and understandable.	Venkatesh et al. (2003); Tseng et al. (2019); Meet et al. (2022); Alghazi et al. (2022); Li et al. (2023)

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Table 2.14 (continue)

Observed Variables	Items	References
Perceived Ease of Use	**EE2:** It would be easy for me to become skillful at using the M-learning.	Venkatesh et al. (2003); Kumar & Bervell (2019); Altalhi (2021); Sidik & Syafar (2020); Shaya, Madani & Mohebi (2023)
	EE3: I would find M-learning easy to use.	Venkatesh et al. (2003); Tseng et al., (2019); Alyoussef (2021); Meet et al. (2022)
Ease of Use	**EE4:** Learning to operate M-learning is easy for me.	Venkatesh et al. (2003); Abbad (2019); Alyoussef (2021); Alghazi et al. (2022); Shaya, Madani & Mohebi (2023)
	EE5: I find it easy to get M-learning to do what I want it to do.	Venkatesh et al. (2003); Shaya, Madani & Mohebi (2023); Li et al. (2023); Abbad (2019)
	EE6: I can easily understand the knowledge points explained by mobile learning.	Bao (2017)
	EE7: Overall, I believe that M-learning is easy to use.	Venkatesh et al. (2003); Alyoussef (2021); Abbad (2019); Kumar & Bervell (2019)

Alghazi et al. (2021) employed UTAUT to explore the factors that affect college students' intention to use mobile learning. To evaluate the proposed model, data from 612 students were analyzed using structural equation modeling (SEM). The results show that factors such as PE, EE, SI, device connectivity, device compatibility and network speed have a significant and positive impact on students' intention to use mobile learning, which confirmed the significance of effort expectancy. This study provides important

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recommendations for university policymakers and developers to understand the factors necessary to adopt mobile learning and reflect student needs.

From the literature, concepts, theories, and researchers conducted on the effort expectancy, the following model was obtained for the effort expectancy, which comprised two observed variables, as shown in figure.

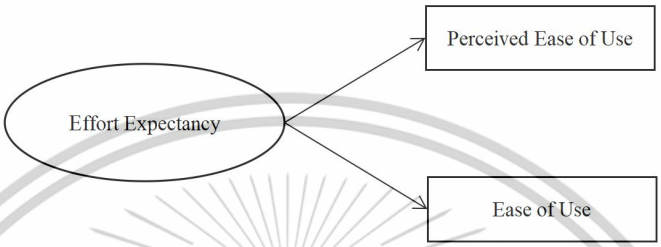

Figure 2.10 Model for Effort Expectancy

Source: Venkatesh et al. (2003)

2.2.5 Social Influence

Venkatesh et al. (2003) define social influence as the extent to which a person believes that important others think that he or she should use a new information system. Three constructs in the existing model capture the concept of social influence: subjective norms (TRA, TAM2, TPB, and C-TAM-TPB), social factors (MPCU), and images (IDT).

Table 2.15 Definition of Social Influence

Scholars/Researchers	Definition
Venkatesh et al. (2012)	The extent that consumers feel other people think they ought to be using a specific technology
Lwoga & Komba (2015)	How people significant to the student, including colleagues, course instructors, institution, government and others believe that the student should continue to use the ICT
Al-Adwan, Al-Adwan & Berger (2018)	the degree to which an individual perceives that others think she/he should use the new system/technology.
Gunasinghe et al. (2020)	external pressure (such as peer or supervisory pressure,

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Table 2.15 (continue)

Scholars/Researchers	Definition
Gunasinghe et al. (2020)	encouragement from the faculty and so on that affect his or her perception on technology.
Yee & Abdullah (2021)	the level to which end users viewed significant others (e.g., family and friends) think that they should utilize a specific technology
Jalil et al. (2022)	an individual's assessment of the importance of accepting a new technological tool, according to others
Nikolopoulou1 et al. (2022).	degree to which students perceive that important others (e.g., friends, peers, university tutors) believe they should use the mobile phone in their studies
Li et al. (2023)	the degree of influence an important person has when suggesting new technologies or systems.

Table 2.15 presented researchers' definitions of social influence. In this study, social influence is defined as the level to which the student is convinced that others think they should make use of mobile learning.

Jalil et al. (2022) examined the factors affecting the behavioral intentions of Malaysian teachers to adopt and use Industry 4.0 (IR4.0) technologies based on the UTAUT model. A questionnaire survey was used to obtain data from a random sample of 62 primary school teachers in Malaysia. The research tested the four main construct of UTAUT model. And results show that only two variables (namely, FC and SI) have a direct impact on the behavioral intention of teachers to use IR4.0 technology. Neither effort nor performance expectancies had an impact on intentions to use these techniques, which were not consistent with many research results. The study concludes with a series of recommendations to improve policy and research on teacher use of IR4 in education. This work showed how these findings can help primary school teachers improve their understanding of 4IR adoption and provide valuable suggestions for 4IR scholars, producers and users.

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Table 2.16 Literature review on Social Influence

Scholars/Researchers	Latent Variable	Observed Variables	Industry
Venkatesh et al. (2003)	Social Influence	1) Subjective Norm 2) Social Factors	Different industries
Venkatesh et al. (2012)	Social Influence	Subjective Norm	Mobile Internet technology
Thomas et al. (2013)	Social Influence	1) Subjective Norm 2) Social Factors	Education (M-Learning)
Al-Adwan, Al-Adwan & Berger (2018)	Social Influence	1) Subjective Norm 2) Social Factors	Education (M-Learning)
Almaiah, Alamri & Al-Rahmi (2019)	Social Influence	Subjective Norm	Education (M-Learning)
Alghazi et al. (2021)	Social Influence	1) Subjective Norm 2) Social Factors	Education (M-Learning)
Meet et al. (2022)	Social Influence	Subjective Norm	Education (MOOCs)
Twum et al. (2022)	Social Influence	1) Subjective Norm 2) Social Factors	Education (E-Learning)
Li et al. (2023)	Social Influence	1) Subjective Norm 2) Social Factors	Education (M-Learning)

Table 2.16 presents a summary of the literature on the social influence. The observed variables of effort expectancy include 1) Subjective Norm, 2) Social Factors. Each of observed variables contains different items as follows.

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Table 2.17 Items of Social Influence

Observed Variables	Items	References
Subjective Norm	**SI1:** People who influence my behaviour think that I should use M-learning.	Venkatesh et al. (2003); Al-Adwan, Al-Adwan & Berger (2018); Alghazi et al. (2022); Li et al. (2023)
	SI2: People who are important to me think that I should use M-learning.	Venkatesh et al. (2003); Al-Adwan, Al-Adwan & Berger (2018); Alghazi et al. (2022); Li et al. (2023)
	SI3: My classmates and teachers think that I should use M-learning.	Altalhi (2021); Botero et al. (2018)
Social Factors	**SI4:** The lecturers and other staff at my college are helpful in the use of M-learning.	Venkatesh et al. (2003); Al-Adwan, Al-Adwan & Berger (2018); Alghazi et al. (2022); Twum et al. (2022); Li et al. (2023)
	SI5: I use M-learning because of the proportion of classmates who use M-learning.	Venkatesh et al. (2003)
	SI6: In general, my college has supported the use of M-learning.	Venkatesh et al. (2003); Al-Adwan, Al-Adwan & Berger (2018); Alghazi et al. (2022)

Twum et al. (2022) studied the factors that influence the behavioral intention to use e-learning during the COVID-19 pandemic. In this study, UTAUT2 model is used to identify

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and predict the factors of e-learning intention by incorporating personal innovation ability and perceived financial cost. This study adopted a cross-sectional quantitative study design, involving 617 college students. Due to the limitations of COVID-19, the data were collected through online surveys. The proposed hypothesis is analyzed by partial least square structural equation model. It is found that personal innovation, perceived financial cost, performance expectancy, hedonic motivation and social influence have a significant impact on intention to use E-learning. Contrary to expectations, habits, effort expectations and faciliting conditions do not predict the intention to use E-learning.

From the literature, concepts, theories, and researchers conducted on the social influence, the following model was obtained for the social influence, which comprised two observed variables, as shown in figure .

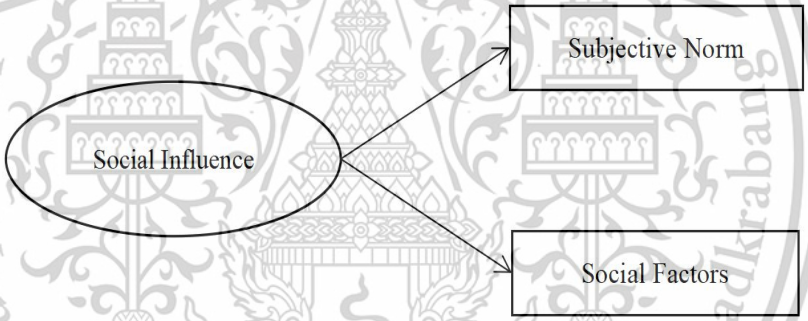

Figure 2.11 Model for Social Influence

Source: Venkatesh et al. (2003)

2.2.6 Facilitating Conditions

Facilitating conditions (FC) is The extent to which individuals believe that there is an organizational and technical infrastructure to support system use (Venkatesh et al., 2003). In other words, facilitating conditions supply the external resources required to make a specific activity easier to complete (Ajzen, 1991). This definition captures concepts embodied by three different constructs: perceived behavioral control (TPBI DTPB, C-TAM-TPB), facilitating conditions (MPCU), and compatibility (IDT). Each of these constructs is operationalized to include aspects of the technological or organizational environment that are designed to remove barriers to use. The availability of training and assistance are considered to be helpful

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circumstances in the context of workplace technology adoption.

Table 2.18 Definition of Facilitating Conditions

Scholars/Researchers	Definition
Venkatesh et al. (2012)	The user belief that institutional support and infrastructure is available to assist in the use of targeted technology.
Lwoga & Komba (2015)	The degree to which students perceive that the institutional and technical infrastructures are available to support the use of ICT
Alshehri et al. (2019)	The individual perception of how well the university provides support in using the innovation.
Nikolopoulou1 et al. (2022)	The degree to which students believe there is sufficient organizational and technical infrastructure, to support the use of mobile phones as supportive-learning tools in their studies
Jalil et al. (2022)	Teachers' perceptions of their ability to acquire the necessary resources and assistance to use IR4.0.

Table 2.18 presented researchers' definitions of facilitating conditions. In this study, facilitating conditions is defined as how confident an individual is about an organizational and technological infrastructure is in place to make mobile learning easier.

Mahande & Malago (2019) aimed to assess the acceptance of e-learning through the UTAUT model by showing the variables influencing the acceptance of e-learning in the graduate program of the University of Negeri, University of Makasar, Indonesia. The data were collected via a questionnaire from 170 students. The results showed that FC, EE, PE, and social influence significantly positively affected behavioral intention, which confirmed the significance of the factor facilitating conditions. FC and BI significantly positively affected the e-learning acceptance. Variables that greatly contributed to the higher or lower

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e-learning acceptance were FC and BI. FC were strongly affected by the students' knowledge and internet speed.

Table 2.19 Literature review on Facilitating Conditions

Scholars/Researchers	**Latent Variable**	**Observed Variables**	**Industry**
Venkatesh et al. (2003)	Facilitating Conditions	1) Perceived Behavioral Control 2) Facilitating conditions	Different industries (Entertainment, banking, et al.)
Venkatesh et al. (2012)	Facilitating Conditions	1) Perceived Behavioral Control 2) Facilitating conditions	Mobile Internet Technology
Abbad (2021)	Facilitating Conditions	1) Perceived Behavioral Control 2) Facilitating conditions	Education (E-learning)
Jalil et al. (2022)	Facilitating Conditions	1) Perceived Behavioral Control 2) Facilitating conditions	Education (IR 4.0 technology)
Wijaya et al. (2022)	Facilitating Conditions	1) Perceived Behavioral Control 2) Facilitating conditions	Education (Micro-lectures)
Li et al. (2023)	Facilitating Conditions	1) Perceived Behavioral Control 2) Facilitating conditions	Education (M-Learning)

Table 2.19 presents a summary of the literature on the facilitating conditions. The observed variables of facilitating conditions include 1) Perceived Behavioral Control; 2) Facilitating conditions. Each of observed variables contains different items as follows.

Table 2.20 Items of Facilitating Conditions

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Observed Variables	Items	References
Perceived Behavioral Control	**FC1:** I have the resources necessary to use M-learning system.	Venkatesh et al. (2003); Almaiah, Alamri & Al-Rahmi (2019); Altalhi (2021); Meet et al. (2022)
	FC2: I have the knowledge necessary to use M-learning system.	Venkatesh et al. (2003); Almaiah, Alamri & Al-Rahmi (2019); Altalhi (2021); Meet et al. (2022)
	FC3: M-learning is compatible with other systems I use.	Meet et al. (2022); Altalhi (2021); Alowayr (2021); Tseng et al., (2019)
Facilitating conditions	**FC4:** There is a specific person or group available for assistance with any technical problem I may encounter.	Venkatesh et al. (2003); Almaiah, Alamri & Al-Rahmi (2019); Altalhi (2021); Meet et al. (2022)
	FC5: Specialized instruction concerning M-learning was available to me.	Venkatesh et al. (2003)
	FC6: Using M-learning fits my learning style.	Venkatesh et al. (2003)
	FC7: I would use M-learning if the teacher included M-learning (such as watching video hours) in the assessment of the course.	Huang (2020)

Wijaya et al. (2022) tried to analyze the behavioral intention (BI) of mathematics teachers in using micro-lectures in mathematics in China, and identify the most influential factors involved for the very first time. The Unified Theory of Acceptance and Use of Technology (UTAUT) model was used as a design model to investigate teachers' behavioral intentions. Online questionnaire was used to collect quantitative data. The participants in the research were 166 mathematics teachers from China. Furthermore, partial least squares (PLS)

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regression was used, and hypothesis testing was performed with the Smart-PLS software. From the results, BI was positively affected by Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI). BI and facility conditions also had positive effects on user behavior; in contrast to other studies, SI had the most significant positive effect on BIs in this study. In this study, FC were found to be predictors of both behavioral intention and use behavior. But in our study, FC is only hypothesized to affect behavioral intention.

From the literature, concepts, theories, and researchers conducted on the facilitating conditions, the following model was obtained for the facilitating conditions, which comprised two observed variables, as shown in figure .

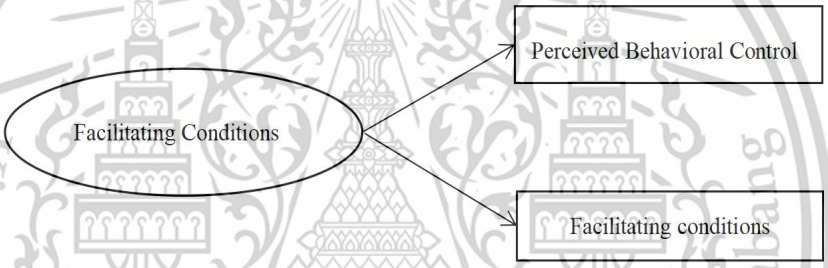

Figure 2.12 Model for Facilitating Conditions

Source: Venkatesh et al. (2003)

2.3 Self-efficacy

Although the original UTAUT model is widely used, many studies have extended the model from different perspectives in order to better adapt to different research topics and produce new research results (Khalilzadeh et al., 2017). This study extends the UTAUT model by combining the Social Cognitive Theory of Bandura (1986).

2.3.1 Social Cognitive Theory

Originated from social psychology, Social Cognitive Theory (SCT) was recognized as a theoretical framework for analyzing the interaction effect of intrinsic psychological motivations and external environmental factors on human behavior (Bandura, 1986). Social cognitive theory has been widely applied in the IS literatures with the rapid change of

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information and technological environment. Zhang et al. (2012) developed a theoretical model to explain students' continuance intention in e-learning systems drawing on social cognitive theory; Rana & Dwivedi (2015) applied social cognitive theory to examine citizens' adoption of an e-government system; while Boateng et al. (2016) adopted social cognitive theory to assess the determinants of individuals' internet banking adoption behavior.

Bandura (1986) introduced the concept of self-efficacy (SE) as a major element of social cognitive theory, and the concept became widespread in multiple areas of education (Islam et al., 2020). Lwoga & Komba (2015) argue that SE is an important factor added to the UTAUT model to measure an individual's ability to use ICT.

2.3.2 Definition of Self-efficacy

Self-efficacy is a concept discovered by Bandura in explaining SCT (Bandura, 1977) and is defined as the personal judgment of how a person is able to execute the course of action needed to respond to future situations filled with multiple unpredictable and stressful factors (Bandura, 1982). In the SCT, self-efficacy is a type of self-assessment that helps the understanding of human behavior and performance in a certain task (Bandura, 1997). As such, self-efficacy theory tries to explain feelings and beliefs of an individual about competency and personal mastery, and the resulting outcomes on behavior adjustment. The greater the confidence an person has about their abilities to perform outcomes, like coping behavior, the greater the possibility of reaching their targets (Bandura, 1986). Self-efficacy is not a measure of skill; rather, it reflects what individuals believe they can do with the skills they possess. In an IT usage context, self-efficacy refers to individuals' judgement of their capability to use IT in diverse situations, but does not refer to simple skill such as copying or restoring data. Rather, it is one's assessment of their capabilities to accomplish complicated tasks (Compeau & Higgins, 1995).

Table 2.21 Definition of Self-efficacy

Scholars/Researchers	Definition
Bandura & Schunk (1981)	One's judgments about how well one can execute various courses of action in diverse prospective situations fraught

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Table 2.21 (continue)

Scholars/Researchers	Definition
Bandura & Schunk (1981)	with several unpredictable and stressful elements
Compeau & Higgins (1995)	The belief that one has the capability to perform a particular behavior
Venkatesh et al. (2003)	the judgment of one's ability to use a technology (e.g. computer) to accomplish a particular job or task
Maillet et al. (2015)	The perception of the degree of comfort using the technology on the own or with help provided in the workplace.
Chavoshi & Hamidi (2019)	Individual's belief in his ability to perform a particular activity.
Yeop et al., (2019)	teachers' perceptions of their beliefs, positive or negative attitudes about their ability to accept, use or implement the Blended learning approach in more effective ways.
Sahin et al. (2022)	An individual's judgment of his/her capacity to perform a learning task through e-learning systems. The belief in the ability to fulfill an educational task with the use of e-learning systems.
Li et al. (2023)	People's evaluation of their effectiveness or ability to execute a specific task.
Shaya, Madani & Mohebi (2023)	Individual ideas and capacities to participate in learning and teaching activities in m-learning.

Table 2.21 presented researchers' definitions of Self-efficacy. In this study, Self-efficacy is defined as students' self-confidence in their capability to perform certain learning tasks with the use of m-learning.

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Yeop et al. (2019) investigated ICT Behavioral Intention (BI) and Use Behavior (UB) factors by employing experience and workload of teachers as moderator. The data were collected through a questionnaire among 720 teachers in Malaysia. The findings showed UE, SI, FC, and teacher efficacy were significant factors affecting BI and UB. Meanwhile, workload factors moderate (1) UE and BI relationships, and (2) TE and BI relationships. This study also provided positive implications for efforts to promote learning practices using a blended learning approach through constructive guidance to policymakers and planning for professional development of teaching.

Table 2.22 Literature review on Self-efficacy

Scholars/Researchers	**Latent Variable**	**Observed Variables**	**Industry**
Lwoga & Komba (2015)	Self-efficacy	1) Confidence 2) Capability	Education (E-Learning)
Chavoshi & Hamidi (2019)	Self-efficacy	1) Confidence 2) Capability	Education (M-Learning)
Almaiah et al. (2019)	Self-efficacy	1) Confidence 2) Qualifications	Education (M-Learning)
Almaiah, Alamri & Al-Rahmi (2020)	Self-efficacy	1) Confidence 2) Qualification	Education (M-Learning)
Alowayr (2021)	Self-efficacy	1) Confidence 2) Capability	Education (M-Learning)
Li et al. (2023)	Self-efficacy	1) To use mobile learning 2) To interact with instructors 3) To interact with classmates	Education (M-Learning)

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Table 2.22 (continue)

Scholars/Researchers	Latent Variable	Observed Variables	Industry
Sahin et al. (2022)	Self-efficacy	1) Confidence 2) Capability	Education (E-Learning)
Shaya, Madani & Mohebi (2023)	Self-efficacy	1) Confidence	Education (M-Learning)
Akbari et al. (2023)	Self-efficacy	1) Confidence 2) Capability	Education (E-Learning)

Table 2.22 presents a summary of the literature on the self-efficacy. This research focuses on mobile learning self-efficacy. The observed variables of self-efficacy include 1) Confidence, 2) Capability. Each of observed variables contains different items as follows.

Table 2.23 Items of Self-efficacy

Observed Variables	Items	References
Confidence	**SE1**: I am confident of using the mobile learning even if there is no one around to show me how to do it.	Venkatesh et al. (2003); Mohammadi (2015); Chavoshi & Hamidi (2019); Altalhi (2021); Shaya, Madani & Mohebi (2023); Akbari et al. (2023)
	SE2: I am confident of using the mobile learning even if I have never used such a system before.	Mohammadi (2015); Chavoshi & Hamidi (2019); Altalhi (2021); Shaya, Madani & Mohebi (2023)
	SE3: I am confident of using the mobile learning even if I have only the online instructions for reference.	Mohammadi (2015); Chavoshi & Hamidi (2019); Altalhi (2021); Shaya, Madani & Mohebi (2023); Akbari et al. (2023)
Capability	**SE4:** I have the ability to use all	Alowayr (2021); Almaiah, Alamri

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Table 2.23 (continue)

Observed Variables	Items	References
	mobile-learning technology features	& Al-Rahmi (2019); Chavoshi & Hamidi (2019)
Capability	**SE5:** I have the ability to post comments and respond to comments posted via mobile learning.	Alowayr (2021); Altalhi (2021)
	SE6: I have the ability to locate information on the course website using mobile learning.	Alowayr (2021); Bin et al. (2020)

Kumar et al. (2020) empirically investigated factors predicting students' behavioral intentions towards the use of mobile learning. The data were collected from 171 engineering undergraduates and analyzed based on structural equation modeling. The results suggest behavioral intention was positively and significantly influenced by mobile learning self-efficacy, attitude, and perceived usefulness, which confirmed the significance of self-efficacy on behavior intention; Mobile learning self-efficacy was only influenced by perceived ease of use. The findings also stipulate a practical reference for higher educational institutions targeting to practice mobile learning for engineering undergraduates.

Based on the literature, theories, concepts, and researchers' findings of the self-efficacy , the latent variable self-efficacy is comprised of two observed variables, as shown in figure .

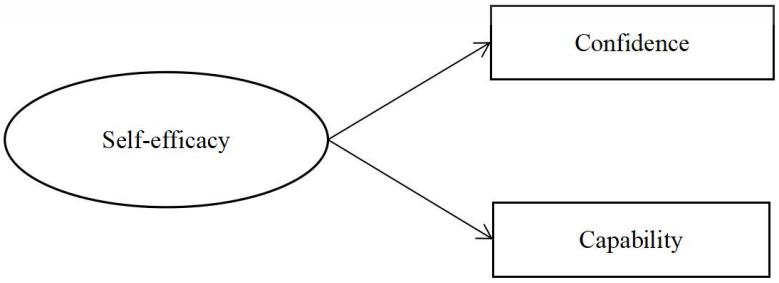

Figure 2.13 Model for Self-efficacy

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Source: Chavoshi & Hamidi (2019)

2.4 Personal Innovativeness

Personal Innovativeness represents an individual's willingness to take a risk and try a new technology (Agarwal & Prasad, 1998). People accept innovations at various rates, which are related to personal comfort. People who are highly innovative are comfortably with new experiences and seek them out, not allowing themselves to be limited by not knowing the outcomes (Lu et al. 2005; Rogers 1995). Individuals that are technically innovative are enthusiastic about new ideas. Furthermore, they frequently test new technology ahead of their peers (Agarwal & Prasad 1998) and exhibit risky behaviors when using new technologies (Kwon et al. 2007). Personal innovativeness in IT is a steady personality feature that encourages people want to try out new technology, according to Farooq et al. (2017). They stated that it is a personal trait that instills the desire and willingness to experiment with new IT advancements.

Table 2.24 Definition of Personal Innovativeness

Scholars/Researchers	Definition
Agarwal & Prasad (1998)	an individual's willingness to take a risk and try a new technology
Schillewaert et al. (2005)	the peoples' perceived predisposition or personal attitude which reflects their tendency to independently experiment and adopt new advancements in information technology
Thakur et al. (2016)	willingness to take chances and to try new things to cope with high levels of uncertainty
Kim, Lee, & Rha (2017)	willingness of an individual to accept innovation earlier than others in terms of a certain product, technology, lifestyle, or consumption pattern
Farooq et al. (2017)	A personal attribute which inculcates the desire and openness to experiment new advancements

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Table 2.24 (continue)

Scholars/Researchers	Definition
Sidik & Syafar (2020)	an individual's willingness to try out any new product or service of information technologies (IT)
Şahin et al. (2022)	the degree to which an individual in a social system adopts an innovation relatively faster and easier than other individuals
Lisana (2023)	the students' willingness to switch and actively use mobile learning in gaining new knowledge

Table 2.24 presented researchers' definitions of personal innovativeness. In this study, personal innovativeness is defined as willingness to adopt latest technology, or risk taking propensity, which might be attached with new features and advancements of mobile learning.

Sidik & Syafar (2020) proposed to explore the factors affecting the willingness of Indonesian university students to use mobile learning systems. To this end, four direct factors included in UTAUT were studied: PE, EE, external influences, service quality, and an additional factor - individual innovation. The study was based on an online survey of 284 respondents. All five surveyed factors significantly influenced students' intentions to use mobile learning, which demonstrated the significant effect of individual innovation on behavior intention of mobile learning. The results suggest that the higher education sector must develop strategic plans and provide guidelines that take into account student intentions to incorporate all key success factors for the sustainable deployment of mobile learning systems.

Table 2.25 Literature review on Personal Innovativeness

Scholars/Researchers	Latent Variable	Observed Variables	Industry
Agarwal & Prasad (1998)	Personal Innovativeness	1) Behaviors 2) States	The World-Wide Web
Farooq et al. (2017)	Personal Innovativeness	1) Behaviors 2) States	Education (E-system)

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Table 2.25 (continue)

Scholars/Researchers	Latent Variable	Observed Variables	Industry
Hao et al. (2017)	Personal Innovativeness	1) Behaviors 2) States	Education (M-Learning)
Kim, Lee, Rha (2017)	Personal Innovativeness	1) Behaviors 2) States	Education (M-Learning)
Sidik & Syafar (2020)	Personal Innovativeness	1) Behaviors 2) States	Education (M-Learning)
Pinho, Franco & Mendes (2021)	Personal Innovativeness	1) Behaviors 2) States	Education (E-Learning)
Sahin et al. (2022)	Personal Innovativeness	1) Behaviors 2) States	Education (E-Learning)
Lisana (2023)	Personal Innovativeness	1) Behaviors 2) States	Education (M-Learning)

Table 2.25 presents a summary of the literature on the personal innovativeness. The measure consists of statements that capture personal innovativeness in the form of behaviors and states (Agarwal & Prasad, 1998). The observed variables of effort expectancy include 1)Behaviors; 2)States. Each of observed variables contains different items as follows.

Table 2.26 Items of Personal Innovativeness

Observed Variables	Items	References
Behaviors	**PI1:** I like to experiment new M-learning technologies.	Thakur et al. (2016); Pinho, Franco & Mendes (2021); Sahin et al. (2022); Lisana (2023)
	PI2: If I heard about a new M-learning technology, I look for ways to experiment with it.	Agarwal & Prasad (1998); Sidik & Syafar (2020); Twum et al. (2022)

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Table 2.26 (continue)

Observed Variables	Items	References
States	**PI3:** Among my peers, I am usually the first to try out new M-learning technology.	Agarwal & Prasad (1998); Hao et al. (2017); Sidik & Syafar (2020); Sahin et al. (2022); Lisana (2023)
	PE4: I am interested in M-learning technologies that are new to me.	Sahin et al. (2022); Lisana (2023)
	PE5： In general, I am hesitant to try out new M-learning technologies (-).	Agarwal & Prasad (1998); Mohammadi (2015); Pinho, Franco & Mendes (2021); Twum et al. (2022)

Lisana (2023) aimed to identify factors that affect switching intention to adopt mobile-learning among university students in Indonesia based on migration theory, Push-PullMooring (PPM) framework. This study used an online survey questionnaire to obtain 616 valid responses. The results revealed that the learning convenience, learning autonomy and enjoyment, and student innovativeness are perceived as significant factors for accepting mobile-learning, which confirmed student innovativeness as important predictor of behavior intention. Furthermore, based on the findings, several recommendations were suggested for the university policy-makers to develop effective strategic plans to get a competitive advantage.

Based on the literature, theories, concepts, and researchers' findings of the personal innovativeness , the latent variable personal innovativeness is comprised of three observed variables, as shown in figure.

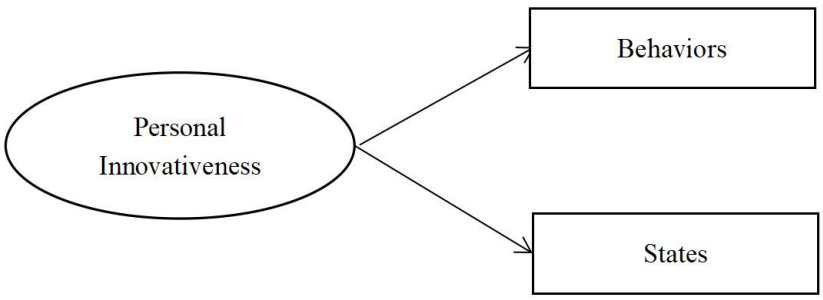

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Figure 2.14 Model for Personal Innovativeness

Source: Sahin et al. (2022)

2.5 Content Quality

2.5.1 Information System Success Model

The DL & ML model developed by DeLone & McLean (2003) has been the most widely used model for IS success. DeLone & McLean (2003) proposed that user satisfaction, intention to use and net benefit were the main components of the model, and three quality factors (system quality, information quality and service quality) were associated with user satisfaction, willingness to use and net benefit. The model was developed with six constructs as shown in Figure 2.15. The causal-impact relationship was the main idea between the constructs relationship. In this model, a system which possesses quality characteristics will lead to a positive experience with use, contributing to more user satisfaction and leading to more intention to use (Delone & Mclean, 2004). According to Hsu et al. (2014), the DeLone and McLean IS Success Model is used for IS research papers as a valid model and framework for variables that are complex dependent. In this regard, a system equipped with quality characteristics will enable the user to have a positive experience and be satisfied, contributing more to their level of intention to use (Delone & Mclean, 2003). Because M-learning systems are a special type of IS in education (Abdullah & Ward, 2016), the D&M model, as one of the most often utilized models for IS success (Almaiah, Jalil & Man, 2016; Almaiah, 2018; Almaiah & Man, 2016), has been broadly implemented as a means of evaluating success in m-learning systems and applied in several empirical studies. Many researchers agree that the factors relating to quality play a vital role in the success of information systems (Althunibat et al., 2022; Arain et al., 2019).

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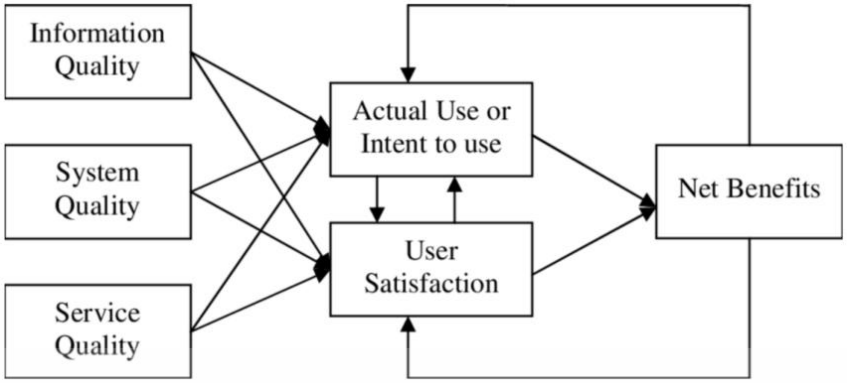

Figure 2.15 Information System Success Model

Source: DeLone & McLean Model (2003)

2.5.2 Definition of Content Quality

Information quality is a key factor in the success of information systems (DeLone & McLean, 1992). In general, information quality refers to the quality, format, and accuracy of information provided by an information system (Almaiah & Alismaiel, 2019). According to DeLone & McLean (1992), the choice of quality factors and dimensions should depend on the context of the study. In the context of information systems in educational Settings (such as e-learning and mobile learning), the most commonly used dimensions of information quality are content quality and content design quality (Cheng 2012; Lee et al. 2009). On this basis, the study takes learning content quality as the quality factor of information quality. In fact, mobile learning has great benefits for learners due to the rich learning content provided by mobile learning applications. The rich content and variety of learning content activities (lectures, discussions, videos, brainstorming, and quizzes) offered by mobile learning apps may make mobile learning feel useful compared to other learning environments (traditional classroom learning and online learning).

Table 2.27 Definition of Content Quality

Scholars/Researchers	Definition
DeLone & McLean (2003)	Measured in terms of accuracy, timeliness, completeness, relevance, and consistency

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Table 2.27 (continue)

Scholars/Researchers	Definition
Yang et al. (2017)	Knowledgeability, authority of course content, and lecturers' teaching attitudes.
Almaiah & Mulhem (2018)	The quality, format, and accuracy of information provided by the system and application
Almaiah, Alamri & Al-Rahmi (2020)	The extent to which complete, accurate, organized, understandable, up to date, and timely information is provided in mobile learning application for users to obtain information about any of their intended services
Pour, Mesrabadi & Asarian (2022)	How much information is understandable to the user and how valid accurate and complete it is.
Alotaibi & Alshahrani (2022)	How the system content is accurate, valid and available.
Çelik & Ayaz (2022)	The characteristics of system outputs such as relevance, intelligibility, accuracy, completeness, timeliness, and usability
Elmunsyah et al. (2023)	Assessed by semantic success measures such as timeliness, accuracy, completeness, consistency and relevance

Table 2.27 presented researchers' definitions of content quality. In this study, we use content quality instead of information quality, which is defined as the suitability of content adequacy, content usefulness, content design when students using mobile learning.

Drawing upon the information systems success model (IS success model) and technology acceptance model, Yang et al. (2017) proposed a theoretical model for studying learners' continuance intentions toward participation in MOOCs. Based on survey data from 294 respondents, structural equation modeling was employed to assess the model. The results of this analysis indicate that system quality, course quality, and service quality were significant antecedents of the continuance intention of individuals, and the effect of course quality and service quality were mediated by perceived usefulness. The results contribute to

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the extant literature in the context of MOOCs learning by identifying the critical quality factors, and provide managerial guidelines for MOOCs utilization and generalization. The implications of the present findings for research and managerial practice are discussed.

Table 2.28 Literature review on Content Quality

Scholars/Researchers	Latent Variable	Observed Variables	Industry
Yang et al. (2017)	Content Quality (Course quality)	1) Informativeness 2) Accessibility	Education (MOOC)
Almaiah & Mulhem (2018)	Content Quality	1) Informativeness 2) Accessibility	Education (M-Learning)
Almaiah & Alismaiel (2019)	Content Quality	1) Informativeness 2) Accessibility	Education (M-Learning)
Almaiah, Alamri & Al-Rahmi (2019)	Content Quality (Information quality)	Informativeness	Education (M-Learning)
Almaiah & Almaiah (2019)	Content Quality (Information quality)	Informativeness	Education M-Learning)
Prasetyo et al. (2021)	Content Quality	1) Informativeness 2) Accessibility	Education (E-learning)
Almaiah et al. (2022)	Content Quality	1) Informativeness 2) Accessibility	Education (M-learning)
Zheng et al. (2023)	Content Quality (Information quality)	1) Informativeness 2) Accessibility	Education (E-Learning)
Elmunsyah et al. (2023)	Content Quality (Information quality)	1) Informativeness 2) Accessibility 3) Usefulness	Education (E-Learning)

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Table 2.28 presents a summary of the literature on the content quality. According to DeLone & McLean (1992), the Iivari-Koskela satisfaction measure included three information quality constructs: "informativeness" which consists of relevance, comprehensiveness, recentness, accuracy, and credibility; "accessibility" which consists of convenience, timeliness, and interpretability; and "adaptability." The observed variables of content quality include 1) Informativeness, 2) Accessibility. Each of observed variables contains different items as follows.

Table 2.29 Items of Content Quality

Observed Variables	**Items**	**References**
Informativeness	**CQ1:** Mobile learning application provides accurate content.	Almaiah & Almaiah (2019); Almaiah, Alamri & Al-Rahmi (2019); Almaiah et al. (2022); Seliana et al. (2020); Elmunsyah et al. (2023);
	CQ2: Mobile learning provides up to date content.	Almaiah & Almaiah (2019); Almaiah, Alamri & Al-Rahmi (2019); Seliana et al. (2020); Almaiah et al. (2022)
	CQ3: Mobile learning provMobile learning application provides up to date content. ides content that is relevant to my needs.	Almaiah & Alismaiel (2019); Almaiah, Alamri & Al-Rahmi (2019); Seliana et al. (2020)
Accessibility	**CQ4:** The content of the course provided by M-learning is easy to understand.	Almaiah, Alamri & Al-Rahmi (2019); Seliana et al. (2020); Zheng et al. (2023);
	CQ5: Mobile learning application provides timely content.	Zheng et al. (2023); Elmunsyah et al. (2023)

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Table 2.29 (continue)

Observed Variables	Items	References
Accessibility	**CQ5:** Mobile learning application provides timely content.	Zheng et al. (2023); Elmunsyah et al. (2023)
	CQ6: It is easy to find the information that I need when using M-learning.	Elmunsyah et al. (2023); Prasetyo et al. (2021)
	CQ7: The course content of mobile learning is more vivid than that of traditional classroom.	Bao (2017)
	CQ8: The course provided by mobile learning can fast forward and play back, which can help us master the whole picture of the knowledge.	Bao (2017)

Almaiah et al. (2022) aimed to identify the crucial factors that could influence the adoption of the Madrasati platform. Online quantitative survey method was employed to collect the data. SEM method was adopted to analyze the hypotheses in the research model. The findings of the study indicate system quality, service quality and content quality, and training have a primary role in increasing the usage of the Madrasati platform in Saudi Arabia, which confirmed the significant effect of content quality on behavior intention. The findings indicate that all factors have a significant influence on Madrasati platform adoption among students. This research contributes to the body of knowledge and Madrasati platform adoption practices.

From the literature, concepts, theories, and researchers conducted on the content quality, the following model was obtained for the social influence, which comprised two observed variables, as shown in figure.

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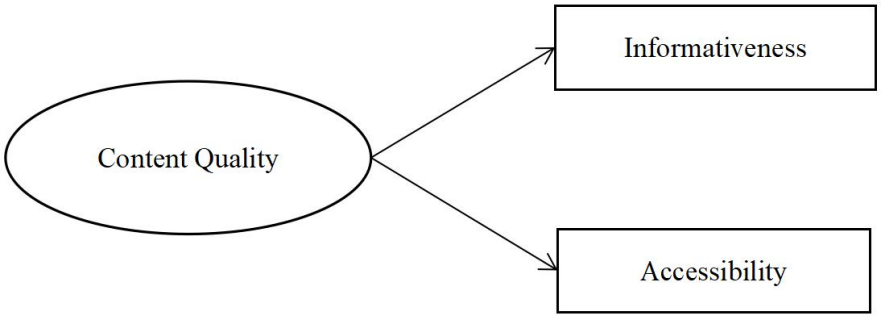

Figure 2.16 Model for content quality

Source: Almaiah & Alismaiel (2019)

2.6 Variables Relationship Analysis

The researcher studied and reviewed the literature in an effort to establish the relationship between the behavioral intention to use M-learning among students. The following sections go over these relationships.

2.6.1 Relationship between PE and BI to use (H1)

Venkatesh et al. (2003) have demonstrated that performance expectancy is the strongest predictor of behavioral intention to use IT. Performance expectations for adapting to mobile learning situations indicate that mobile learners will find mobile learning useful because it enables learners to complete learning activities more flexibly and quickly, and even helps to improve their learning efficiency. Al-Adwan, Al-Adwan & Berger (2018) claimed that individuals' effort and performance expectancy significantly influence their intentions. Lwoga & Komba (2015) showed that the more students believe that the use of e-learning technologies would result in better achievements in their course programme, the more they will continue to use the e-learning platform. Kaliisa et al. (2017) also identified the same trend in their study. Other researchers (Almaiah & Mulhem, 2019; Nikolopoulou, 2018; Botero et al., 2018) have implemented the UTAUT model, and data supports the idea that performance expectancy and behavioral intention to use are positively related.

Al-Adwan, Al-Adwan & Berger (2018) proposed a framework that is based on UTAUT model to explore the potential factors that may impact students' intention to acceptance and use of m-learning in developing countries like Jordan. The researchers extended UTAUT

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model to by adding 3 variables (trust expectancy, self-management of learning, system functionality), as presented in below.

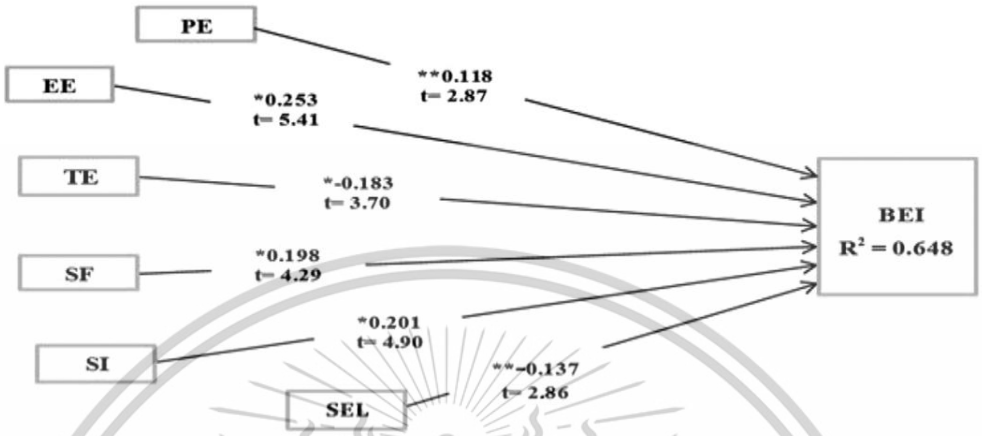

Figure 2.17 UTAUT Model with additional variables

Source: Al-Adwan, Al-Adwan & Berger (2018)

The proposed framework was empirically tested using a total of 444 paper questionnaires collected from students at four Jordanian universities. The results show that EE, PE, trust expectations, learning self-management, system functionality, and SI are important determinants of mobile learning adoption and explain 64.8% of the variation in students' willingness to adopt mobile learning. It is found that gender and uncertainty avoidance have a moderating effect on some relationships in the study model. These findings provide multiple useful implications for the adoption of mobile learning in both research and practice.

Considering the unified theory of acceptance and use of technology (UTAUT) as a theoretical background, Alowayr (2021) investigated the factors that affect learners' acceptance of m-learning in Saudi Arabia. The research framework extended the UTAUT by including intrinsic motivation, mobile learning self-efficacy and perceived satisfaction. A total of 200 higher education students voluntarily participated in the research. The application of the partial least square technique indicated that the proposed model can predict m-learning adoption adequately in Saudi Arabia. The results showed that performance expectancy, subjective norm and perceived satisfaction significantly affected behavioral intention. The research outcomes are significant for educational institutions and teachers to implement

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M-learning effectively. Many recommendations can be suggested to help enhance learners' willingness to adopt m-learning technology: Teachers need to design their courses in an interactive way and provide several different activities to ensure that learners obtain real benefits in their learning outcomes.

GovindAarajan & Krishnan (2019) explored the influence of the Web Quality (WQ) and Self-Efficacy (SE) on massive open online courses technology adoption by extending the UTAUT model. Two new constructs Web Quality (WQ) and Self Efficacy (SE) were added to the existing UTAUT model. The study was conducted among college students who use MOOC and hence the sampling technique used was purposive sampling. The statistical tools used for analysis of the data are cross-tabulation and regression. The research revealed that performance expectancy, effort expectancy, social influence,web quality, and self-efficacy has significant influence on behavioral intention to use MOOC. The implication of this research is that the service providers get more light on the important factors which influence the behavioral intention to use MOOCs and to know the technology acceptance of MOOC.

From above the literature, it is hypothesized that performance expectancy will have a significant influence on students' behavioral intention to use mobile learning.

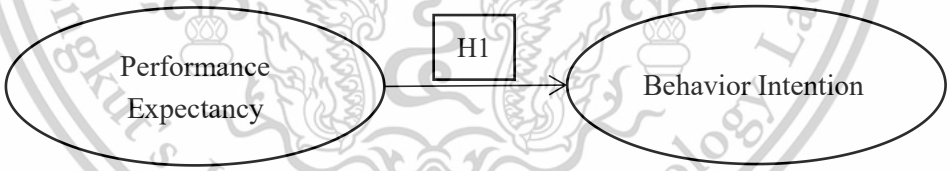

Figure 2.18 Performance Expectancy and Behavior Intention

2.6.2 Relationship between EE and BI to use (H2)

Previous studies on technology adoption have shown that in the initial stage of technology adoption, effort expectations are significant in both voluntary and involuntary environments, and effort expectations become less significant over time of continuous usage (Venkatesh, 2000). This means that the more students believe that the e-learning platform would be easy to use, the more they would continue to use it in future (Lwoga & Komba, 2015). From a technology adoption perspective, the expected workload is key because technology users must have the skills and capabilities to use the system. The expected

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workload explains the simplicity and convenience of using the technology (Thongsri et al., 2018). Students' perceptions of the ease of use of the system will encourage them to develop their intention to use the system. Tarhini et al. (2017) support that students find the system easy to use, then they are more likely to use it. Many similar studies (Nikolopoulou, 2018; Kaliisa et al., 2017) find evidence to support the idea that effort expectations and behavioral intent are closely related.

Chao (2019) empirically tested a model to predict the factors that affect students' behavioral intentions using mobile learning. This study explores behavioral intent using mobile learning by applying an extended UTAUT model and adding moderators of perceived enjoyment, mobile self-efficacy, satisfaction, trust, and perceived risk. A cross-sectional study was conducted using research models based on multiple technology acceptance theories. The data came from an online survey of 1,562 respondents and was analyzed using structural equation models. Partial least squares (MIS) regression was used for model and hypothesis testing. The results show that behavioral intention is significantly and positively affected by satisfaction, trust, performance expectation and effort expectation. Mobile self-efficacy has a significant positive effect on perceived enjoyment; Perceived risk has a significant negative moderating effect on the relationship between performance expectation and behavioral intention. Our findings are consistent with the UTAUT model and provide a practical reference for educational institutions and policymakers involved in designing mobile learning implementations at universities.

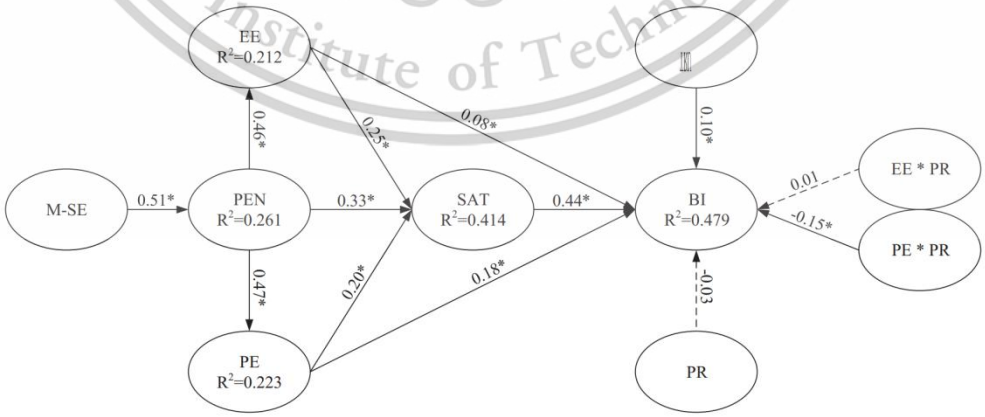

Figure 2.19 Extended UTAUT model

Source: Chao (2019)

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From above the literature, it is hypothesized that effort expectancy will have a significant influence on students' behavioral intention to use mobile learning.

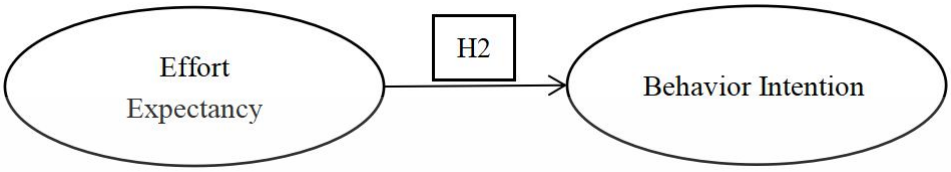

Figure 2.20 Effort Expectancy and Behavior Intention

2.6.3 Relationship between SI and BI to use (H3)

Previous research has shown that social influence plays an important role in shaping individuals' intentions to use new technologies (Thompson et al., 1991; Venkatesh & Davis, 2000). Research has shown that social influence can significantly predict the adoption of technology in both voluntary and coercive Settings (Venkatesh et al., 2003). This effect has been seen in web-based learning (Lwoga & Komba, 2015), e-learning (Mahande & Malago, 2019), and teacher professional learning (Dunn et al., 2018). The direct effect of social influence on behavioral intent is plausible because people may be influenced by the opinions of others to engage in a certain behavior, even if they do not want to (Tarhini et al., 2017). Lutfi (2022) argues that people who are important to the individual may influence their final decision. Arain et al. (2019) found that students are influenced by others on social networks when it comes to using mobile learning services. Users perceive social impact as a social advantage arising from the use of new technologies (Al-Adwan, Al-Madadha, & Zvirzdinaite, 2018). From a mobile learning perspective, many studies have shown that students' decisions to use mobile learning are significantly influenced by significant individuals such as peer students and/or teachers (Yeap et al., 2016; Wang et al., 2009; Abu-Al-Aish & Love, 2013).

Alshehri et al. (2019) adopted the UTAUT model to study how people accept and use the Blackboard system. The sample for the study was taken from students in Saudi higher education. A total number of 171 questionnaires were used in this study. The data were analyzed using Structural Equation Modelling (SEM) techniques to test the hypothesized

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research model. The findings illustrated that the performance expectancy, social influence and technical support had a significant impact on behavioral intention. In the study, facilitating condition and technical support were found to be the predictors of the Blackboard system use. The findings of the study may help to provide insights into a better approach to promote e-learning acceptance.

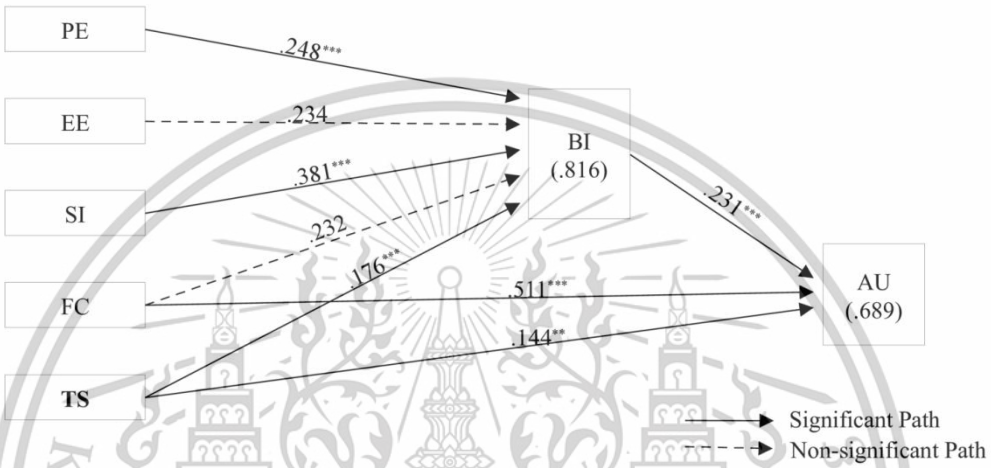

Figure 2.21: Extended UTAUT model

Source: Alshehri et al. (2019)

From above the literature, it is hypothesized that social influence will have a significant influence on students' behavioral intention to use mobile learning.

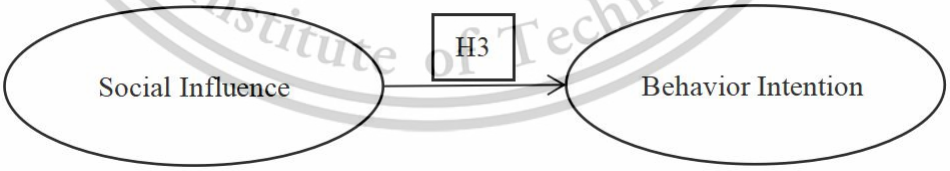

Figure 2.22 Social Influence and Behavior Intention

2.6.4 Relationship between FC and BI to use (H4)

Facilitating conditions affect both actual usage (Venkatesh et al., 2003) and user intention (Venkatesh et al., 2012). Although, the original UTAUT shows that facilitating conditions have significant impacts on actual usage only, other studies such as a meta-analysis

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of 43 technology acceptance studies revealed that facilitating conditions had positive impacts on behavioral intention as well (Dwivedi et al., 2011). Moreover, prior studies on e-learning acceptance show that facilitating conditions have positive effects on continued usage intention (Bakar et al. 2013). Indications are that the better the organizational and technical support and ICT infrastructure as perceived by students, the more they will continue to use the e-learning system (Lwoga & Komba, 2015). In the model of UTAUT, the impact of facilitating conditions was significant (Venkatesh et al., 2003). The evidence can also be found in study of Sung et al. (2015), which applied the UTAUT model to investigate the acceptance of mobile learning services. They revealed that facilitating conditions were beneficial to behavioral intention to adopt mobile learning system. Many researchers (Meet et al., 2022; Almaiah, Alamri & Al-Rahmi, 2019; Al-Adwan, Al-Madadha & Zvirzdinaite, 2018) revealed that facilitating conditions significantly influenced behavioral intention to use mobile learning system. Hence, it is critical to examine whether facilitating conditions have a direct influence on the adoption of the mobile learning, as the absences of facilitating resources may result in barriers to usage (Wang, 2016).

Meet et al. (2022) explored the factors affecting the behavioral intention to adopt MOOCs among Generation Z enrolled in the Indian HEIs. The study used the extended UTAUT2 model with additional constructs of language competency and teacher influence. Using online survey, data of 483 students was collected from HEIs of India using stratified random sampling and analyzed using partial least square-structure equation modelling (PLS-SEM) technique. The results established the general applicability of UTAUT2 model with explanatory power of 69.9% and highlights the positive influence of price value, hedonic motivation, facilitating conditions, performance expectancy and effort expectancy on MOOC adoption. However, the constructs of social influence, habit, language competency, and teacher influence unexpectedly do not have an impact on Behavioral Intention.

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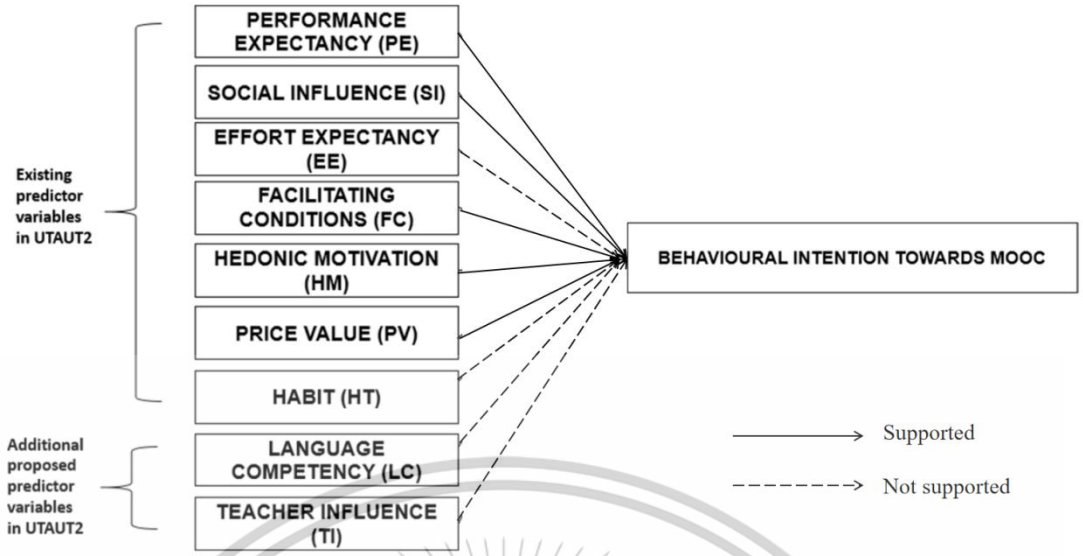

Figure 2.23 Extended UTAUT2 model

Source: Meet et al. (2022)

Al-Adwan,Al-Madadha & Zvirzdinaite (2018) investigate the the effect of several factors on students' intention to use m-learning in higher education in Jordan. A total of 228 questionnaires were acceptable for analysis. This empirical study collected data from students using paper questionnaires. The results show that students' intention to adopt mobile learning is influenced by several factors, including comparative advantage, complexity, social influence, facilitating conditions, perceived pleasure, and self-management of learning. By providing students' willingness to adopt mobile learning, this study provides useful and beneficial implications for developers of mobile learning applications as well as education providers to guide the design and implementation of integrated mobile learning systems.

From above the literature, it is hypothesized that facilitating conditions will have a significant influence on students' behavioral intention to use mobile learning.

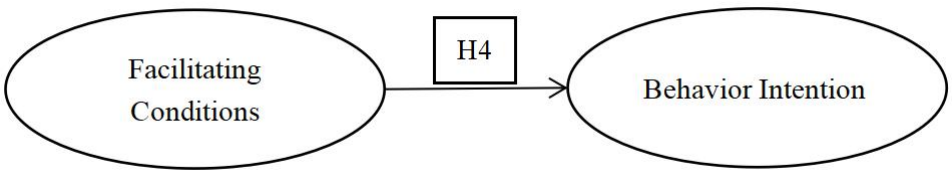

Figure 2.24 Facilitating Conditions and Behavior Intention

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2.6.5 Relationship between SE, BI to use and UB (direct and indirect, H5-10)

According to the theory of planned behavior (TPB), a person's self-efficacy will reinforce his or her behavior (Ajzen, 1991; Fishbein & Ajzen, 1973). Previous research has found that a person's self-efficacy affects how much time they spend on the Internet (Compeau & Higgins, 1995; Agarwal & Karahanna, 2000). Compeau & Higgins (1995) state that people having higher self-efficacy are less likely to be frustrated or discouraged by obstacles and are more likely to overcome them due to their persistence. An individual with higher self-efficacy is likely to have higher perceived usefulness, ease of use, and willingness to utilize it. Venkatesh et al. (2003) claimed that self-efficacy was an indirect factor captured by EE and completely mediated by EE through additional research. As a result, they eliminated MSE as a direct predictor of behavior. A person with a higher self-efficacy perceives to be capable of handling computerrelated work with less support and would be competent to use different systems (Wangpipatwong et al., 2008). Self-efficacy has been shown to be one of the most critical variables in determining whether or not an educational system is accepted (Al-Emran et al., 2018; Almaiah et al., 2019; Chavoshi & Hamidi, 2019; Almaiah & Alismaiel, 2019).

(1)SE and BI (H5)

Compeau and Higgins (1995) pointed out that the higher the self-efficacy of personal computers, the deeper people's feelings for computers, the less anxiety about computers, and the overall self-efficacy of users has a positive impact on the use of computers. Chavoshi and Hamidi (2019) stated that self-efficacy factors has a positive influence on continues intention to use of m-learning system. As for mobile learning, Mahdi (2014) found a significant relationship between self-efficacy and intention in e-learning for university students, using the extended TAM model.

Mohammadi (2015) explores the factors that influence user intent and satisfaction, as well as the mediating effect of availability on mobile learning use in Iran. A total of 390 questionnaires were collected from students at four public universities in Tehran. Based on the mobile learning user data collected by the survey, structural equation modeling (TEM) and path analysis were used to test the research model. The results show that both intent and user

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satisfaction predict the AU of mobile learning. Subjective norms, perceived image, usefulness, innovation, SE, and personal mobility were found to be important anthems of users' intention. At the same time, this paper attempts to conduct a literature review of the recently published research in mobile learning.

From above the literature, it is hypothesized that self-efficacy will have a significant influence on students' behavioral intention to use mobile learning.

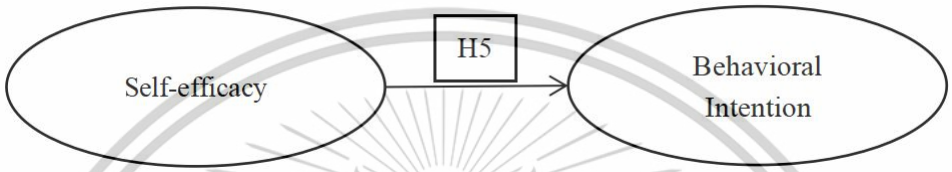

Figure 2.25 Self-efficacy and Behavior Intention

(2)SE and UB (H6)

Compeau & Higgins (1995) state that people having higher self-efficacy are unlikely to be frustrated or discouraged by barriers and are more likely to get over them owing to their perseverance. A person with a higher self-efficacy perceives to be capable of handling computerrelated work with less support and would be competent to use different systems (Wangpipatwong et al., 2008). That means an individual with higher self-efficacy is likely to have higher perceived usefulness, ease of use, and willingness to use it. Padumadasa (2012) found self-efficacy as an important determinant of the users' actual usage of e-learning system. Indications are that the more students believe that they have the ability to operate in e-learning environment, the more they will use the e-learning systems (Lwoga & Komba, 2015). The findings of a survey of 697 university students revealed that self-efficacy is one of the most important motivators for students' adoption of m-learning systems and, as a result, the success of m-learning projects execution (Almaiah, Alamri & Al-Rahmi, 2019).

Lwoga & Komba (2015) examined factors that predict students' continued usage intention of web-based learning management systems (LMS) in Tanzania, with a specific focus at the School of Business of Mzumbe University (MU). Specifically, the study investigated major predictors of actual usage and continued usage intentions of e-learning system, and challenges of using the e-learning system. Data was collected through a

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questionnaire survey to 300 third year undergraduate students, with a rate of return of 77%. A total of 20 faculty members were also interviewed. The unified theory of acceptance and use of technology (UTAUT) was utilized in the study. The results show that actual usage was determined by self-efficacy, while continued usage intentions of web-based learning system was predicted by performance expectancy, effort expectancy, social influence, self-efficacy and actual usage.

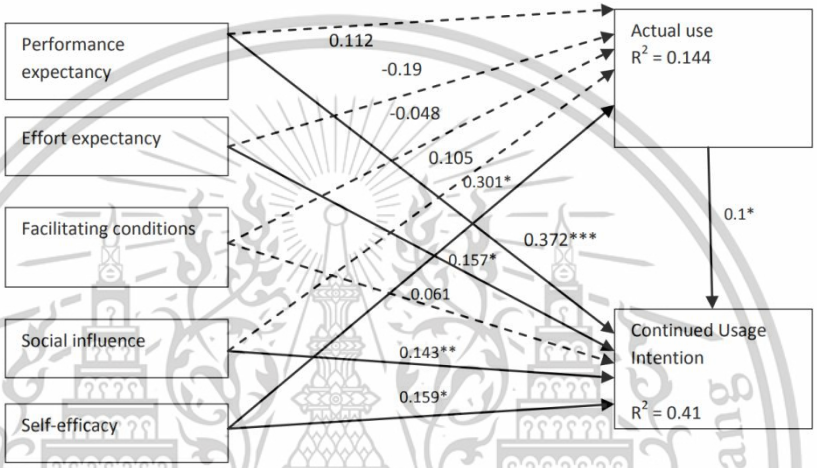

Figure 2.26 Extended UTAUT model

Source: Lwoga & Komba (2015)

From above the literature, it is hypothesized that self-efficacy will have a significant influence on students' actual use of mobile learning.

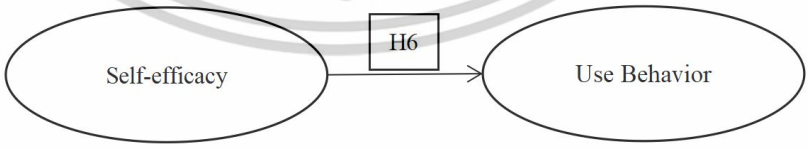

Figure 2.27 Self-efficacy and Use Behavior

(3)SE and PE, EE, FC, SI (H7-H10)

For mobile learning, Wang & Xing (2019) and Zheng & Li (2020) reported that effort expectancy and performance expectancy were significantly influenced by the self-efficacy of elementary, undergraduate and postgraduate students while students receiving higher

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vocational education were not included in the research. Li et al. (2023) incorporating self-efficacy into the UTAUT model, found that self-efficacy has significant influence on effort and performance expectancies, social influence and Facilitating conditions. Reserachers (Shaya, Madani & Mohebi, 2023; Altalhi, 2021) claimed that SE had a substantial influence on PE and EE.

Shaya, Madani & Mohebi (2023) examined a theoretical model to predict the factors affecting students' acceptance and behavioral intentions of using mobile learning in United Arab Emirates. This study explored the BI to use mobile learning by applying UTAUT model incorporating service quality, perceived enjoyment and mobile self-efficacy and satisfaction. The data was collected from an online survey with 395 respondents. The results revealed that satisfaction significantly influenced BI. Perceived enjoyment, service quality and mobile SE significantly affected PE and EE. SEM analysis showed that satisfaction was central to users' BI and mediated the effects of PE and EE on behavioral intentions.

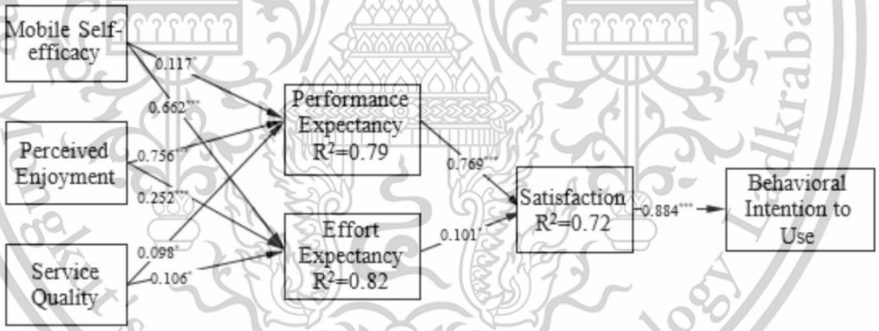

Figure 2.28 Extended UTAUT model

Source: Shaya, Madani & Mohebi (2023)

Li et al. (2023) carried out a study to examine students' acceptance of mobile learning by UTAUT. The proposed model added self-efficacy into original. A total sample of 900 students from higher vocational colleges were selected to participate in and their responses were analyzed using SEM to validate the extended UTAUT. The results provide significant evidence of the sub-dimensions of self-efficacy and confirm the validity of extended UTAUT. The results showed that PE,SI and FC significantly impact the intention to use mobile learning. The research incorporated SE into the UTAUT model and found that SE has

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significant influence on effort and performance expectancies, SI and FC. Meanwhile, the mediating effects of PE, SI, and FC were found between SE and intention to use mobile learning.

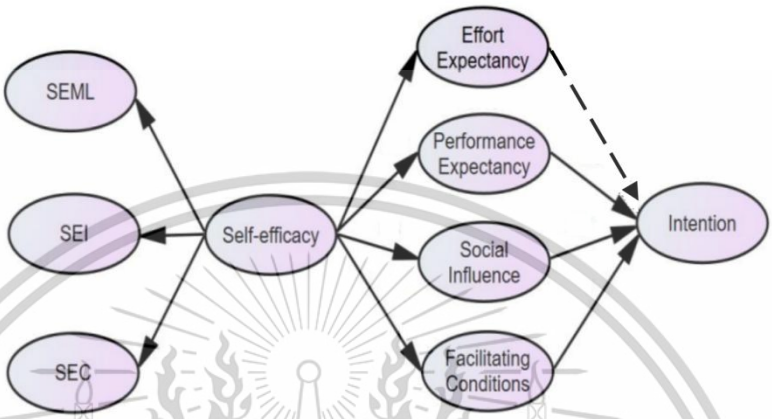

Figure 2.29 Extended UTAUT model

Source: Li et al. (2023)

From above the literature, it is hypothesized that self-efficacy will have a significant influence on EE, PE, SI and FC.

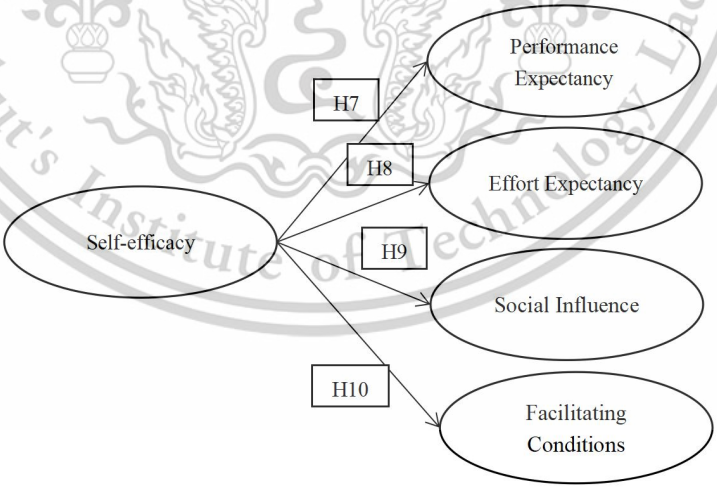

Figure 2.30 Self-efficacy and 4 constructs (EE, PE, SI and FC)

2.6.6 Relationship between PI, BI and UB (H11, H12)

Personal innovativeness in the domain of information technology have an undeniable relation with technology adoption in end used. Prior studies confirmed that the personal trait

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factor strongly affects innovation technology adoption behavior in various contexts, such as internet-only banks (Yoon & Lim, 2021), and both augmented and virtual reality (Kim et al., 2020). In the context of mobile learning, highly innovative students are expected to have a more positive intention to incorporate mobile learning as an innovative method into their learning process. The more receptive to new technologies and inventive consumers are, the more sensitive they are. In summary, more inventive users are more likely to embrace new technology (Hong et al., 2021; Alhussain et al., 2020).

(1) PI and BI (H11)

An individual's receptivity toward taking chances or trying new things should lead to his/ her desire for innovativeness. Individuals with a high level of innovativeness enjoy and appreciate the use of high-tech devices and services, because they tend to take more risks than others (Thakur et al., 2016). It has been proven that those with high levels of innovativeness tend to be more interested in acquiring knowledge regarding high-tech products and using new technologies (Lee & Rha, 2016). Kim, Lee, Rha (2017) found that innovativeness had a significant impact on students' intention to use mobile learning. Evidences are confirmed in various studies (Lisana et al., 2023; Alturki & Aldraiweesh, 2022; Sidik & Syafar, 2020; Farooq et al., 2017; Ahmad & Love, 2013).

Kim, Lee, & Rha (2017) studied the factors that predict college students' resistance and intention to use mobile learning by developing a comprehensive research model that combines innovation diffusion theory (IDT) and innovation resistance model (MIR). They add the concept of inertia and innovation to the personal aspects of student adoption of mobile learning. The structural equation results show that relative advantage, complexity and inertia have significant effects on students' mobile learning resistance, among which inertia is the most significant. Relative advantage, innovation and resistance to mobile learning have significant effects on students' willingness to use mobile learning, among which comparative advantage is the most significant. The findings provide valuable implications for researchers and educational practitioners to develop and implement appropriate mobile learning strategies.

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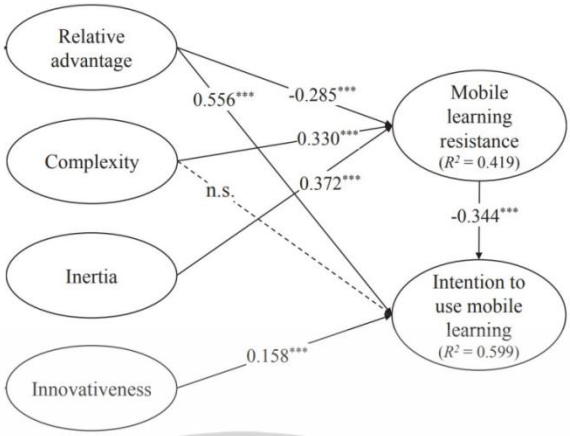

Figure 2.31 Research model that combines IDT and MIR

Source: Kim, Lee, & Rha (2017)

Alturki & Aldraiweesh (2022) aimed to examine students' satisfaction with their behavioral intention to use mobile learning, as well as their perceptions of their actual use of mobile learning during the COVID-19 pandemic in higher education. The research is based on the Technology Acceptance Model (TAM). The satisfaction and behavioral intentions of students to utilize mobile learning to make real use of mobile education was measured using four separate variables. A TAM survey was used to collect the majority of the data, with questionnaires being randomly distributed to 300 students from King Saud University. SPSS and Smart-PLS3.3.3 were used to analyze the data. The results in terms of the students' satisfaction and behavior intention show that M-learning has a good and constructive influence on the actual usage of M-learning. Personal innovativeness, Task-technology Fit, Perceived Ease of Use, Perceived Usefulness and Students' Satisfaction are reported to influence behavior intention. As a result, students are encouraged to use M-learning in their classrooms and to collaborate with their peers at higher education institutions. The study's empirical findings aid in the integration of the TAM model in order to increase students' M-learning performance.

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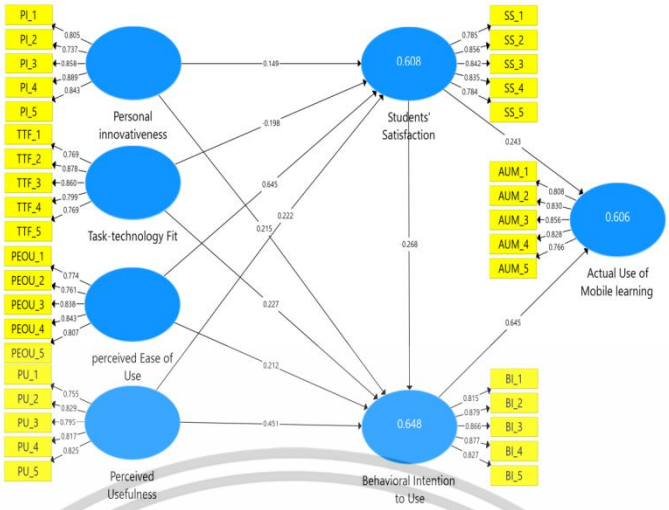

Figure 2.32 the extended TAM model

Source: Alturki & Aldraiweesh (2022)

From above the literature, it is hypothesized that Personal innovativeness will have a significant influence on students' behavioral intention to use mobile learning.

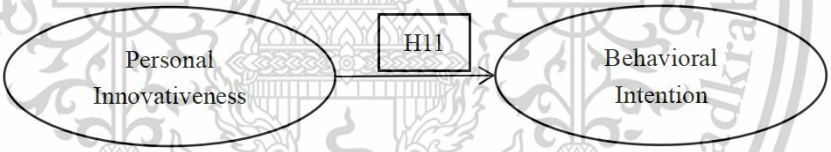

Figure 2.33 Personal Innovativeness and Behavior Intention

(2) PI and UB (H12)

Individuals with a high levels of PIIT tend to develop a more positive attitude towards new IT and tend to use it more quickly than those with lower levels (Agarwal & Prasad 1998; Ahmad & Love, 2013), meaning that highly innovative individuals are more willing to adopt new IT in their daily routine and cope well with the uncertainties arising from its use (Lee et al. 2007). In the context of mobile learning, highly innovative students are expected to have a more positive intention to incorporate mobile learning as an innovative method into their learning process. The more receptive to new technologies and inventive consumers are, the more sensitive they are. In summary, more inventive users are more likely to embrace new

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technology (Hong et al., 2021; Alhussain et al., 2020). PI positively influenced use behaviour (Farooq et al., 2017; Pinho, Franco & Mendes, 2021).

Farooq et al. (2017) investigated the perception and behaviour of executive business students towards acceptance and use of lecture capture system (LCS). The study aims to explore the causal relationship between existing structures for UTAUT2, individual innovativeness (PI). A total number of 481 respondents from executive business school students from the offshore campuses of five selected foreign universities in Malaysia wwere used to test the proposed theoretical model. The results of SEM show that PE, EE, SI, FC, price value, hedonic motivation, habit and personal innovative (PI) have significant effects on the use of LCS.

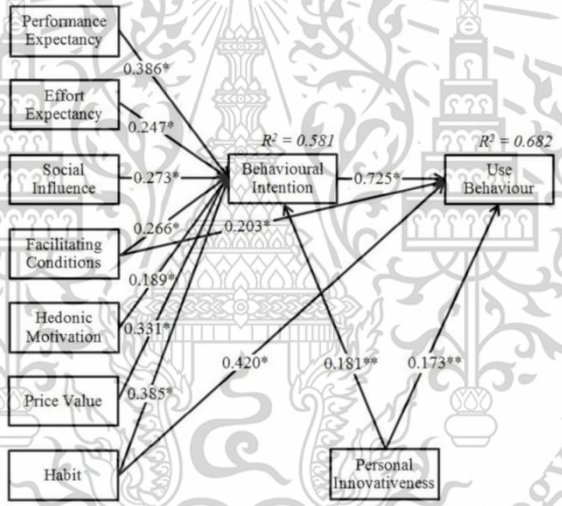

Figure 2.34 the extended UTAUT2 model

Source: Farooq et al. (2017)

Pinho, Franco & Mendes (2021) aimed to identify the factors influencing the use of Moodle as a Learning Management Systems (LMS) in the academic context. A quantitative study was carried out through a questionnaire directed to Portuguese university students, which obtained a total of 631 valid answers. The results obtained, based on structural equation modelling, show that the characteristics of Moodle LMS and Personal Innovativeness in Information Technology influence the use of this tool positively. This research contributes to advancing the literature on this subject, and for practice the importance of elaborating

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student-centred LMS is highlighted. These and other implications and suggestions for future research are also presented.

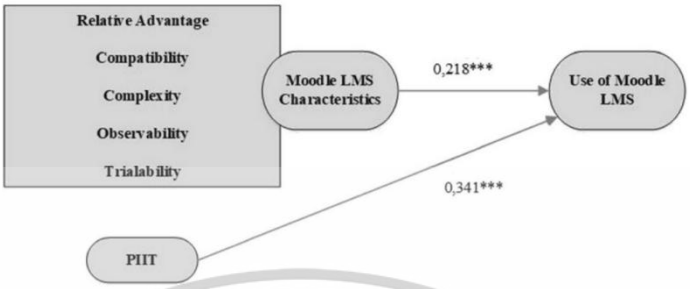

Figure 2.35 the extended IDT model

Source: Pinho, Franco & Mendes (2021)

From above the literature, it is hypothesized that personal innovativeness will have a significant influence on students' use behavior.

Figure 2.36 Personal Innovativeness and Use Behavior

2.6.7 Relationship between CQ, BI and UB (H13-H14)

Content quality is a major determinant of IS and m-learning performance, and it has a crucial role in achieving learning objectives and addressing the challenges resulting from low information quality (Petter et al.,2008). Quality learning content and materials need to have precision, accuracy, and timely, suitable, and updated elements. The content information has an important role in achieving learning objectives and the severe challenges that have occurred as a result of low content quality (Alsabawy, 2016). Researchers who have dedicated their work to the variable's influence (Almaiah & Alismaiel, 2019; Almaiah & Mulhem, 2019) contend that content quality plays a major role in forming the satisfaction of students with their m-learning-system usage.

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(1) CQ and BI (H13)

Content Quality is measured by relevance, scope, accuracy, timeliness, completeness, and efficiency of content (Arain et al., 2019； Cheng, 2012). In fact, mobile learning has great benefits for students due to the rich learning content provided by mobile learning applications. According to Mohammadi (2015), information quality is one of the most critical factors and plays a crucial role in determining the success of educational technology systems. Almaiah, Jalil, & Man (2016) reveal that content quality has a significant impact on the acceptance of mobile learning systems. Similarly, many researchers identified that information quality has a significant relationship with intention toward m-learning usage (Seliana et al., 2020; Lutfi et al., 2022; Yudiawan et al. 2022; Jami, Mesrabadi & Asarian, 2022).

Almaiah & Alismaiel (2018) integrated the TAM with the updated DL&ML model to examine whether quality factors (including system quality, information quality, and service quality) and individual beliefs (including perceived usefulness and perceived ease of use) are the predictors to students' satisfaction and their intention to use, leading to enhancing their actual usage of mobile learning system. A total of 400 questionnaires were distributed. The results showed that the three quality factors had significant effects on students' satisfaction and their intention to use mobile learning; besides, perceived usefulness has significantly strong impacts on intention to use mobile learning, and satisfaction and intention to use both have significant effects on actual use of mobile learning.

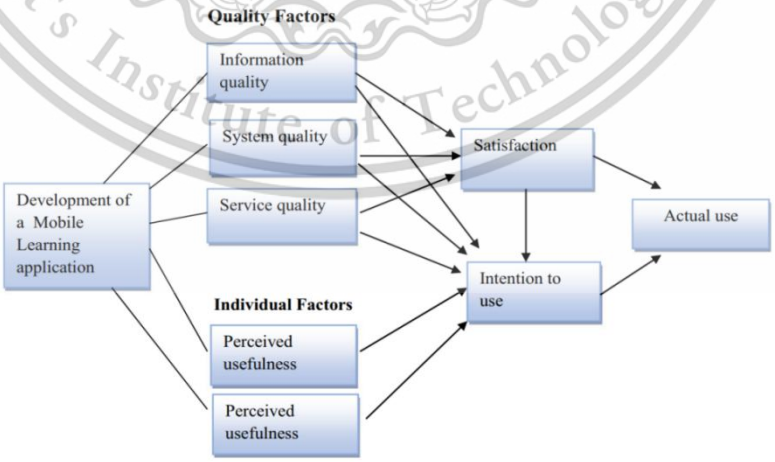

Figure 2.37 Research model combining TAM and DL&ML model

Source: Almaiah & Alismaiel (2018)

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From above the literature, it is hypothesized that Content Quality will have a significant influence on students' behavioral intention to use mobile learning.

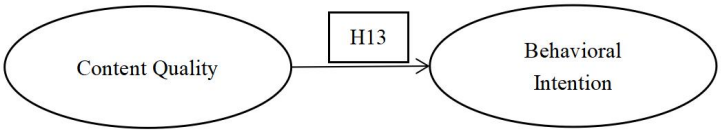

Figure 2.38 Content Quality and Behavior Intention

(2) **CQ and UB (H14)**

Content quality is a major determinant of IS and m-learning performance, and it has a crucial role in achieving learning objectives and addressing the challenges resulting from low content quality (Lutfi et al., 2022). M-learning systems need to present sufficient, accurate, and useful learning materials enriched with multimedia content, enabling learners to search for and conduct their learning activities with ease. Researchers who have dedicated their work to the variable's influence (Almaiah & Alismaie, 2019; Almaiah & Mulhem, 2019) contend that content quality plays a major role in forming the satisfaction of students with their m-learning usage. Elmunsyah et al. (2023) revealed that information quality had significant effect on acceptance of a mobile learning system. Similarly, Çelik & Ayaz (2022) had a significant effect on use of Student Information System.

Cidral et al. (2018) investigated the determinants of user perceived satisfaction, use, and individual impact of e-learning. The study proposed a theoretical model integrating theories of information systems' satisfaction and success in the e-learning systems. The model was empirically validated in higher education institutions and university centers in Brazil through a quantitative method of structural equation modeling. Collaboration quality, information quality, and user perceived satisfaction explain e-learning use. The drivers of user perceived satisfaction are information quality, system quality, instructor attitude toward e-learning, diversity in assessment, and learner perceived interaction with others. System quality, use, and user perceived satisfaction explain individual impact.

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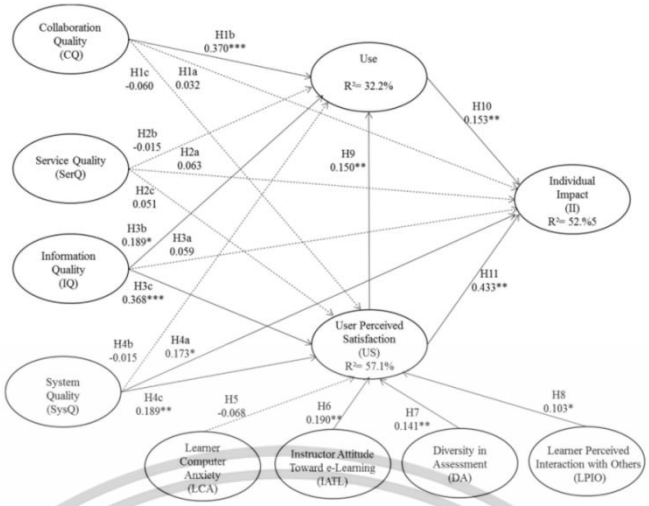

Figure 2.39 the extended IS success model

Source: Cidral et al. (2018)

Almaiah & Alyoussef (2019) aimed to investigate the main determinants that affect the usage and acceptance of e-learning systems among Saudi students. The study utilized UTAUT model and introduced new factors. A total of 507 undergraduate and postgraduate students at King Faisal University were selected to participate in this research. The findings revealed that course design, course content support, course assessment and instructor characteristics had a significant effect on the actual use of e-learning systems. However, the influence of SI on actual use was found to be statistically insignificant.

From above the literature, it is hypothesized that Content quality will have a significant influence on students' use behavior of mobile learning.

Figure 2.40 Content Quality and Use Behavior

2.6.8 Relationship between BI to use and UB (H15)

There is a large number of published studies confirming the significant positive relationship between BI and usage behaviour (Davis, 1989; Bin et al., 2020; Botero et al., 2018; Prasetyo et al., 2021; Almaiah, Alamri & Al-Rahmi, 2019; Alshehri, Rutter & Smith,

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2019). The positive relationship between intention to use and actual use of technology was supported by Venkatesh et al. (2003; 2012) as well.

Prasetyo et al. (2021) investigated the factors for acceptance of an online learning platform among students during the COVID-19 pandemic. A total of 500 senior high school students voluntarily participated to answer constructs under the Extended Technology Acceptance Model (ETAM) and Delone and McLean IS Success Model. The results indicated that PEU was found to have the greatest on actual use (AU), followed by UI and SQ towards PEU, which subsequently led to BI and AU. IQ was found to have a significant effect on PU, which led to BI and AU. BI was found to have a significant effect on AU. Finally, the model construct can be applied and utilized to analyze the online learning platforms in other countries.

From above the literature, it is hypothesized that behavioral intention will have a significant influence on students' use behavior of mobile learning.

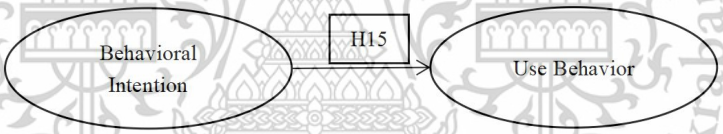

Figure 2.41 Behavioral Intention and Use Behavior

The literature review of the relationship between the variables is summarized in table 2.30.

Table 2.30 Summaries of relationships between variables

Hypothesis	Relationships	References
H1	PE → BI	Almaiah, Alamri & Al-Rahmi (2019); Tarhini et al. (2021); Li et al. (2022); Meet, Kala & Al- Adwan (2022); Milošević et al. (2015); Sidik & Syafar (2020); Farooq et al. (2017); Gunasinghe et al. (2020); Alshehri, Rutter & Smith (2019); Al-Adwan, Al-Adwan & Berger, (2018); Sidik & Syafar (2020); Ameri et al., (2019)

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Table 2.30 (continue)

Hypothesis	Relationships	References
H2	EE → BI	Meet, Kala & Al- Adwan (2022); Tarhini et al. (2021); Sidik & Syafar (2020); Gunasinghe et al. (2020); Almaiah, Alamri & Al-Rahmi (2019); Farooq et al. (2017); Al-Adwan, Al-Adwan & Berger, (2018); Sidik & Syafar (2020);
H3	SI → BI	Tarhini et al. (2021); Farooq et al. (2017); Alshehri, Rutter & Smith, (2019); Yeop et al., (2019); Al-Adwan, Al-Madadha & Zvirzdinaite (2018); Jalil et al. (2022); Li et al. (2022); Al-Adwan, Al-Adwan & Berger, (2018); Sidik & Syafar (2020); Ameri et al., (2019)
H4	FC → BI	Almaiah, Alamri & Al-Rahmi (2019);Yeop et al., (2019); Lutfi et al. (2022); Meet, Kala & Al- Adwan (2022); Al-Adwan, Al-Madadha & Zvirzdinaite (2018); Farooq et al. (2017); Gunasinghe et al. (2020); Jalil et al. (2022); Li et al. (2022);
H5	SE → BI	Tarhini et al. (2021); Kumar et al. (2020); Almaiah, Alamri & Al-Rahmi (2019); Yeop et al., (2019); Mohammadi (2015); Mahdi (2014); Fianu et al. (2018)
H6	SE → UB	Rahmawati (2019); Lwoga & Komba (2015); Almaiah, Alamri & Al-Rahmi (2019)
H7	SE → PE	Shaya, Madani & Mohebi (2023); Li et al. (2022); Zheng & Li (2020); Althunibat (2015); Altalhi (2020); Al-Azawei et al., (2017); Bin et al. (2020);
H8	SE → EE	Shaya, Madani & Mohebi (2023); Li et al. (2022); Zheng and Li (2020); Althunibat (2015); Altalhi (2020); Al-Azawei et al., (2017); Bin et al. (2020); Wong Muhammad & Abdullah (2020);

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Table 2.30 (continue)

Hypothesis	Relationships	References
H9	SE → FC	Li et al. (2022); Yeap, Ramayah, & Soto-Acosta (2016); Zolait (2015)
H10	SE → SI	Li et al. (2022); Kumar et al. (2020); Wong Muhammad & Abdullah (2020);
H11	PI → BI	Kim, Lee, Rha (2017); Milošević et al. (2015); Ahmad & Love (2013); Lisana et al. (2023); Alturki & Aldraiweesh (2022); Sidik & Syafar (2020); Farooq et al. (2017); Aish & Love (2013);
H12	PI → UB	Farooq et al. (2017); Pinho, Franco & Mendes (2021); Larsen & Sorebo (2005)
H13	CQ → BI	Almaiah & Alismaiel (2019); Lutfi et al. (2022); Jami, Mesrabadi & Asarian (2022); Almaiah & Mulhem (2019);
H14	CQ → UB	Almaiah, Alamri & Al-Rahmi (2019); Seliana, Suroso & Yuliati (2020); Elmunsyah et al. (2023); Çelik & Ayaz (2022); Cidral et al. (2018);
H15	BI → UB	Almaiah, Alamri & Al-Rahmi (2019); Almaiah & Alismaiel (2019); Lutfi et al. (2022); Farooq et al. (2017); Gunasinghe et al. (2020); Davis, (1989); Bin et al. (2020); Botero et al. (2018); Alshehri, Rutter & Smith, (2019)

2.7 Conceptual framework

From the analysis of the literature review, and the consultation of the concepts, theories, and models regarding the relationship between variables, the following conceptual framework is developed.

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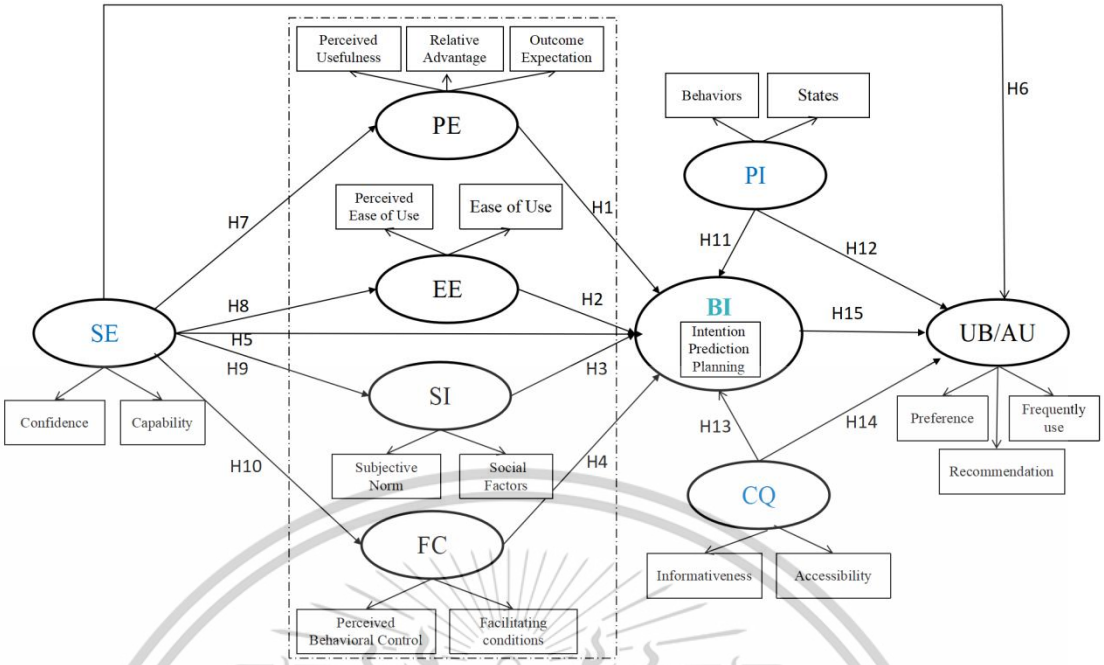

Figure 2.42 Conceptual framework of this study

The conceptual framework above shows that the dependent variables is behavioral intention and use behavior of mobile learning. The independent variables contain performance expectancy(PE), effort expectancy(EE), social influence(SI), facilitating conditions(FC), self-efficacy(SE), personal innovativeness (PI) and content quality (CQ). From the above conceptual framework, the following hypotheses are developed.

H1: Performance Expectancy will positively influence behavioral intention to use mobile learning;

H2: Effort Expectancy will positively influence Behavioral Intention to use mobile learning;

H3: Social Influence will positively influence Behavioral Intention to use mobile learning;

H4: Facilitating Conditions will positively influence Behavioral Intention to use mobile learning;

H5: Self-Efficacy will positively influence Behavioral Intention to use mobile learning;

H6: Self-Efficacy will positively influence Use Behavior of mobile learning;

H7: Self-Efficacy will positively influence Performance Expectancy;

H8: Self-Efficacy will positively influence Effort Expectancy;

H9: Self-Efficacy will positively influence Social Influence;

H10: Self-Efficacy will positively influence Facilitating Conditions;

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H11: Personal Innovativeness will positively influence Behavioral Intention to use mobile learning;

H12: Personal Innovativeness will positively influence Use Behavior of mobile learning;

H13: Content Quality will positively influence Behavioral Intention to use mobile learning;

H14: Content Quality will positively influence Use Behavior of mobile learning;

H15: Behavioral Intention will positively influence Use Behavior of mobile learning.

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CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This research aims to investigate the factors affecting the students' intention to use the mobile learning in the higher vocational colleges in China. The research was designed to adopt the extended UTAUT model by incorporating three variables, self-efficacy, personal innovativeness and content quality. The quantitative approach was used to carry out the research study. With regard to quantitative research, the primary data was collected using questionnaires from a sample size of 630 respondents. The structural equation model (SEM) was applied to analyze the data.

The guideline of this chapter is as follows.

3.2 Population and Sample

3.3 Sample size and sampling design

3.4 Variables

3.5 Research instruments development

3.6 Quality of the instruments

3.6.1 Validity of the Instruments

3.6.2 Reliability of the Instruments

3.7 Data collection

3.8 Data analysis

3.9 Statistical analysis

3.10 Ethical Consideration

3.11 Conclusion

The research procedure is presented in the following steps.

Step 1: This step involves the review of the relevant literature, theories, articles, online statistics, and academic papers, which helped in building this study. It helped in selecting the study variables, identifying the research problem, and specifying the research gap. From the

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study, the research objectives and research questions were developed, helping in solving the research problems identified and bridging the research gaps. This led to the development of the conceptual framework, which contains 9 latent variables and 21 observed variables.

Step 2: This step is quantitative research. The data collected from the respondents were filtered, tested for reliability and validity. Then the structural equation model was conducted. Then the results were presented. The conclusions were made from the quantitative research.

The process can be seen in details as following.

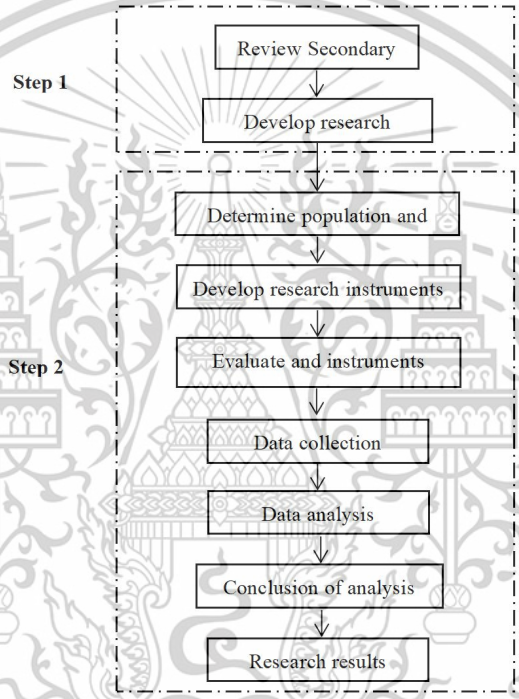

Figure 3.1 Research procedure

3.2 Population and Sample

The population of the research was the students in the higher vocational college in China, who have used mobile learning in different courses (Students should have taken the course for at least one semester). If the students do not finish the first semester,they do not answer the questionnaires. According to “2023 Vocational Education Quality Annual Report”, there are 1545 vocational colleges, 14.5568 million students in mainland China. Since the population is so large, a representative sample was developed. The sample of the research was students who use mobile learning applications in higher vocational colleges from different regions.

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3.3 Sample size and sampling design

Hair et al. (2006) regard five respondents per variable to be analyzed as the lower limit, but the most acceptable way of determination is the 20:1 ratio (20 samples for one variable). Since this study has 21 observed variables, the appropriate sample size is at least 420. Considering the large population of college students in China, the sample size of this study is 1.5 times the minimum sample size, that is 630.

The study has adopted the random sampling design to obtain the sample, because it gives an equal chance to be included in the study sample. Mainland China can be divided into 7 regions. They are Northeast, North, Northwest, the Central, East, Southwest, South. The college student number in each region is collected to get the proportion of each region. Multiplied by the sample size, sample size of each region is obtained. The results are shown in table 3.1. The selected colleges are the top 10 colleges in each region. The primary data to be used in this research is collected using online questionnaire through social media.

Table 3.1 the population and sample size

Region	Students number (thousand)	Proportion	Sample size
Northeast	998.5	6.86%	43
North	1541.8	10.59%	67
Northwest	980.5	6.74%	42
Central	2558.6	17.58%	111
East	4108.3	28.22%	178
Southwest	2298.1	15.79%	99
South	2071	14.23%	90
Total	14556.8	100%	630

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3.4 Variables

In this study, there are 9 latent variables and 21 observed variables.

3.4.1 The exogenous latent variables including observed variables as listed:

h) Performance expectancy

- Perceived usefulness
- Relative advantage
- Outcome expectation

i) Effort expectancy

- Perceived Ease of Use
- Ease of Use.

j) Social influence

- Subjective Norm
- Social Factors

k) Facilitating conditions

- Perceived Behavioral Control
- Facilitating conditions

l) Self-efficacy

- Confidence
- Capability

m) Personal innovativeness

- Behaviors
- States

n) Content quality

- Informativeness
- Accessibility

3.4.2 The endogenous latent variables including observed variables as listed:

c) Behavioral intention

- Intention to use technology
- Planning to use technology

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- Prediction to use technology

d) Use behavior

- Preference
- Frequently use
- Recommendation

3.5 Research instruments development

1. Develop and prepare research questionnaire structures from relevant theories, literature, concepts, and researches.

2. The evaluated models, theories, concepts lead to the development of the relationships between the endogenous variables, the exogenous variables and the observed variables.

3. The questionnaire, which was used to collect data, was compliant with there commended structure. Check the item-objective congruence (IOC) of the questionnaire. IOC will help in evaluating the congruence among the questions included in the questionnaire and their ability to address the research objectives and questions. The expected level of acceptance is between 0.5 - 1.0. When IOC value is lower than 0.5, the questions must be improved in order to fit for objectives and questions of study (Turner & Carlson, 2009).

4. The questionnaire was used in Chinese language to collect the datasets with a 5-point Likert scale. The translation was done by 3 Chinese doctoral students fluent in English with a strong research background to avoid any shortcomings. The Translated version of questionnaire revisions were certified 3 experts to ensure the translations are in perfect order.

5. The internal consistency or the reliability of the collected data was tested using Cronbach's alpha. This test is used when the questionnaire used in research has Likert questions. The scale is considered to be good reliability when Cronbach's alpha is greater than 0.7.

The questionnaire was divided into five sections:

Part 1: Demographic information- this section was collected the personal data of the respondents such as age, gender, grade and region. This was aimed to capture the demographic characteristics of the respondents.

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Part 2: Questions about internet knowledge and experience of the respondents.

Part 3: Questions on the latent and observed variables of the UTAUT model from mobile learning perspective.

1. Use behavior

Instruction: Please choose the most match in your opinion by filling into five levels of the scale

Table 3.2 Questions on Use behavior

	Question	Least → Most				
		1	2	3	4	5
7	**Preference:** I prefer to use M-learning when available.					
8	I aim to use M-learning instead of traditional ones.					
9	**Frequently use:** I use M-learning Frequently .					
10	I use M-learning daily.					
11	I will use M-learning frequently in the future.					
12	**Recommendation:** I recommend M-learning for others to use.					

2. Behavioral intention

Table 3.3 Questions on Behavioral intention

Question		Least → Most				
		1	2	3	4	5
13	**Intention:** I intend to use M-learning in the future.					
14	**Prediction:** I predict I would use M-learning in the future.					

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Table 3.3 (continue)

15	**Planning:** I plan to use M-learning in the future.	

3. Performance Expectancy

Table 3.4 Questions on Performance Expectancy

	Question	Least → Most				
		1	2	3	4	5
16	**Perceived Usefulness:** I find M-learning useful in my learning.					
17	Using M-learning would make it easier for my learning.					
18	Using M-learning would improve my learning performance.					
19	Using mobile learning would help me prepare before class and review after class.					
20	**Relative Advantage:** Using the M-learning enables me to accomplish tasks more quickly.					
21	Using the M-learning increases my productivity.					
22	Using M-learning system increases the quality of learning process.					
23	**Outcome Expectation:** Using a M-learning platform will increase my chances of learning things that are important to me.					
24	If I use M-learning, my classmates will perceive me as competent.					
25	Using M-learning will increase my chances of getting a better grade.					

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4. Effort Expectancy

Table 3.5 Questions on Effort Expectancy

	Question	Least → Most				
		1	2	3	4	5
	Perceived Ease of Use：					
26	My interaction with M-learning would be clear and understandable.					
27	It would be easy for me to become skillful at using the M-learning.					
28	I would find M-learning easy to use.					
29	**Ease of Use：** Learning to operate M-learning is easy for me.					
30	I find it easy to get M-learning to do what I want it to do.					
31	I can easily understand the knowledge points explained by mobile learning.					
32	Overall, I believe that M-learning is easy to use.					

5. Social Influence

Table 3.6 Questions on Social Influence

	Question	Least → Most				
		1	2	3	4	5
	Subjective Norm：					
33	People who influence my behaviour think that I should use M-learning.					
34	People who are important to me think that I should use M-learning.					

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Table 3.6 (continue)

	Question	Least → Most				
		1	2	3	4	5
35	My classmates and teachers think that I should use M-learning.					
	Social Factors：					
36	The lecturers and other staff at my college are helpful in the use of M-learning.					
37	I use M-learning because of the proportion of classmates who use M-learning.					
38	In general, my college has supported the use of mobile learning.					

6. Facilitating Conditions

Table 3.7 Questions on Facilitating Conditions

	Question	Least → Most				
		1	2	3	4	5
	Perceived Behavioral Control:					
39	I have the resources necessary to use M-learning system.					
40	I have the knowledge necessary to use M-learning system.					
41	M-learning is compatible with other systems I use.					
	Facilitating conditions：					
42	There is a specific person or group available for assistance with any technical problem I may encounter.					

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Table 3.7 (continue)

	Question	Least → Most				
		1	2	3	4	5
43	Specialized instruction concerning M-learning was available to me.					
44	Using M-learning fits my learning style.					
45	I would use M-learning if the teacher included M-learning (watching video hours) in the assessment of the course.					

Part 4: Questions about Self-efficacy, Personal Innovativeness and Content Quality from mobile learning perspective.

7. Self-efficacy

Table 3.8 Questions on Self-efficacy

	Question	Least → Most				
		1	2	3	4	5
	Confidence：					
46	I am confident of using the mobile learning even if there is no one around to show me how to do it.					
47	I am confident of using the mobile learning even if I have never used such a system before.					
48	I am confident of using the mobile learning even if I have only the online instructions for reference.					
	Capability：					
49	I have the ability to use all mobile-learning technology features.					

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Table 3.8 (continue)

	Question	Least → Most				
		1	2	3	4	5
50	I have the ability to post comments and respond to comments posted via mobile learning.					
51	I have the ability to locate information on the course website using mobile learning.					

8. Personal Innovativeness

Table 3.9 Questions on Personal Innovativeness

	Question	Least → Most				
		1	2	3	4	5
52	**Behaviors:** I like to experiment new M-learning technologies.					
53	If I heard about a new M-learning technology, I look for ways to experiment with it.					
54	**States:** Among my peers, I am usually the first to try out new M-learning technology.					
55	I am interested in M-learning technologies that are new to me.					
56	In general, I am hesitant to try out new M-learning technologies (-).					

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9. Content Quality

Table 3.10 Questions on Content Quality

	Question	Least → Most				
		1	2	3	4	5
57	**Informativeness:** Mobile learning application provides accurate content.					
58	Mobile learning application provides up to date content.					
59	Mobile learning provides content that is relevant to my needs.					
60	**Accessibility:** The content of the course provided by mobile learning is easy to understand.					
61	Mobile learning application provides timely content.					
62	It is easy to find the information that I need when using M-learning.					
63	The course content of mobile learning is more vivid than that of traditional classroom.					
64	The course provided by mobile learning can fast forward and play back, which can help us master the whole picture of the knowledge.					

Prat 5: suggestions of respondents

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The questionnaire used for the study was structured as shown in the table below.

Table 3.11 Questionnaire structure

Variable	Total Questions	Question Number	Form/Scale
Part 1: Demographic information	4	1-4	Nominal scale
Part 2: Questions on the internet knowledge and experience	2	5-6	Ratio and Interval scale
Part 3: Use behavior			
Preference	2	7-8	Likert Scale
Frequently use	3	9-11	
Recommendation	1	12	
Behavioral intention			
Intention to use technology	1	13	Likert Scale
Planning to use technology	1	14	
Prediction to use technology	1	15	
Performance expectancy			
Perceived usefulness	4	16-19	Likert Scale
Relative advantage	3	20-22	
Outcome expectation	3	23-25	
Effort expectancy			
Perceived Ease of Use	3	26-28	Likert Scale
Ease of Use	4	29-32	
Social influence			
Subjective Norm	3	33-35	Likert Scale
Social Factors	3	36-38	
Facilitating Conditions			
Perceived Behavioral Control	3	39-41	Likert Scale
Facilitating conditions	4	42-45	

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Table 3.11 (continue)

Variable	Total Questions	Question Number	Form/Scale
Part 4: Self-efficacy			
Confidence	3	46-48	Likert Scale
Capability	3	49-51	
Personal innovativeness			
Behaviors	2	52-53	Likert Scale
States	3	54-56	
Content quality			
Informativeness	3	57-59	Likert Scale
Accessibility	5	60-64	
Part 5: Suggestions of respondents			

The questionnaire was developed in relation to the research questions and in reference to the conceptual framework. The literature review was also consulted to in form the items designed for each observed variable. The scale development of the latent and observed variables is presented in the following table.

Table 3.12 Development of scale

Latent variable	Observed variables	Development of research variables	No. of questions
Use behavior	1) Preference 2) Frequently use 3) Recommendation	Abbad (2021); Altalhi (2021); Alyoussef (2021); Bin et al. (2020); Almaiah, Alamri & Al-Rahmi (2019); Almaiah & Alismaiel (2019); Al-Adwan, Al-Adwan & Berger (2018); Islam (2016); Mohammadi (2015);	6

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Table 3.12 (continue)

Latent variable	Observed variables	Development of research variables	No. of questions
Behavioral Intention	1) Intention to use 2) Predicting to use 3) Planning to use	Venkatesh et al. (2003); Li et al. (2023); Shaya, Madani & Mohebi (2023); Meet et al. (2022); Tseng et al., (2019); Almaiah et al. (2019); Fagan (2019); Al-Adwan, Al-Madadha & Zvirzdinaite (2018); Thomas et al. (2013);	3
Performance Expectancy	1) Perceived usefulness 2) Relative advantage 3) Outcome expectation	Venkatesh et al. (2003); Venkatesh et al. (2012); Li et al. (2023); Shaya, Madani & Mohebi (2023); Meet et al. (2022); Alghazi et al. (2022); Abbad (2021); Huang (2020); Sidik & Syafar (2020); Almaiah, Alamri & Al-Rahmi (2019); Tseng et al., (2019); Chao (2019); Al-Adwan, Al-Adwan & Berger (2018)	10
Effort Expectancy	1) Perceived Ease of Use 2) Ease of Use	Venkatesh et al. (2003); Venkatesh et al. (2012); Li et al. (2023); Shaya, Madani & Mohebi (2023); Meet et al. (2022); Alghazi et al. (2022); Sidik & Syafar (2020); Altalhi (2021); Alyoussef (2021); Tseng et al. (2019); Kumar & Bervell (2019); Abbad (2019); Al-Adwan, Al-Adwan & Berger (2018); Bao (2017); Thomas et al. (2013);	7

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Table 3.12 (continue)

Latent variable	Observed variables	Development of research variables	No. of questions
Social Influence	1) Subjective Norm 2) Social Factors	Venkatesh et al. (2003); Venkatesh et al. (2012); Li et al. (2023); Alghazi et al. (2022); Twum et al. (2022); Meet et al. (2022); Altalhi (2021); Almaiah, Alamri & Al-Rahmi (2019) Al-Adwan, Al-Adwan & Berger (2018); Botero et al. (2018); Thomas et al. (2013);	6
Facilitating Conditions	1) Perceived Behavioral Control 2) Facilitating conditions	Venkatesh et al. (2003); Venkatesh et al. (2012); Li et al. (2023); Meet et al. (2022); Wijaya et al. (2022); Jalil et al. (2022); Altalhi (2021); Alowayr (2021); Huang (2020); Almaiah, Alamri & Al-Rahmi (2019); Abbad (2019);	7
Self-efficacy	1) Confidence 2) Capability	Venkatesh et al. (2003); Shaya, Madani & Mohebi (2023); Li et al. (2023); Akbari et al. (2023); Chavoshi & Sahin et al. (2022); Altalhi (2021); Alowayr (2021); Bin et al. (2020); Hamidi (2019); Almaiah, Alamri & Al-Rahmi (2019); Mohammadi (2015); Lwoga & Komba (2015)	6
Personal Innovativeness	1) Behaviors 2) States	Agarwal & Prasad (1998); Lisana (2023); Sahin et al. (2022); Twum et al. (2022); Pinho, Franco & Mendes (2021); Sidik & Syafar (2020); Hao et al. (2017); Thakur et al. (2016); Mohammadi (2015);	5

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Table 3.12 (continue)

Latent variable	Observed variables	Development of research variables	No. of questions
Content Quality	1) Informativeness 2) Accessibility	Zheng et al. (2023); Elmunsyah et al. (2023); Almaiah et al. (2022); Prasetyo et al. (2021); Seliana et al. (2020); Almaiah & Almaiah (2019); Almaiah, Alamri & Al-Rahmi (2019); Bao (2017)	8

The analysis data were obtained from the questions, which were designed with a 5-point Likert Scale. These questions were developed according to the previous literature and other academicians. The 5-point Likert scale was containing the following components:

5'- Strongly Agree

4' - Agree

3'- Neutral (Neither Agree nor Disagree)

2'- Disagree

1'- Strongly Disagree

The 5-point rating levels are interpreted based on the calculation of the compliance class interval and classification principle. Consequently, the distance of each interval is used in the assessment criteria for the variables, as shown in Table 3.

Table 3.13 Qualitative Rating

Score Interval	Evaluation Criteria
4.21-5.00	Strongly Agree
3.41-4.20	Agree
2.61-3.40	Neutral (Neither Agree nor Disagree)
1.81-2.60	Disagree
1.00-1.80	Strongly Disagree

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3.6 Quality of the instruments

It was important to evaluate whether the instrument used to collect data for the research was in quality standard. To check the quality standard of the instruments, the validity and reliability was evaluated as discussed in the following sections.

3.6.1 Validity of the Instruments

The index of item-objective congruence developed by Rovinelli & Hambleton (1977) is a procedure used in test development for evaluating content validity at the item development stage. A team of 3 experts, as academicians and executives, who have used mobile learning applications were asked to evaluate whether the questions were appropriate, and whether any improvements are needed. In addition to this evaluation, there was the instrument calculation for the IOC between each question and variables. The questions, which had an IOC greater than 0.5 were considered appropriate. The calculation process is presented as following:

$$IOC = \frac{\sum r}{N}$$

Where N = number of experts

r = Congruence value of each Question

The IOC ranges from -1 to 1. Hence, a question was considered good when it is the close to l. The questions having IOC less than 0.6 should be revised. Those with IOC less than 0.5 should be excluded from the questionnaire (Turner & Carlson, 2009). The range of IOC included:

- 1: The experts agree that the questions are in accordance with the content.
- 0: The experts are not confident that the questions are in accordance with the content.
- -1: The experts agree that the questions are not in accordance with the content

The IOC standards criterion was as follows.

- The validity factor of questions with IOC values between 0.5 and 1.00.
- Questions with an IOC value of less than 0.5 must be changed and cannot be included.

Item “How long do you use mobile learning?” got a score of 0.66 and is improved with clarity to “How long have you used M-learning?”. To distinguish the item “I use M-learning

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frequently" and item "I use M-learning daily", we change the first one into "I use M-learning sometimes". So the two items would look differently. After revision, all items passed the IOC requirement and were considered to be suitable for the survey.

3.6.2 Reliability of the Instruments

Cronbach's alpha was calculated to evaluate reliability of the instrument. Cronbach's alpha greater than 0.7 was considered acceptable (Gliem & Gliem, 2003). The formula for developing the Cronbcah's alpha is presented by (Gliem & Gliem,2003). The coefficient of alpha ranges from 0 to 1, as presented in the table below. The higher the Cronbach's alpha, the better the reliability of the questions.

The formula of Cronbach's alpha is present below:

$$\alpha = \frac{K}{K-1}\left(1 - \frac{\sum S_i^2}{S_t^2}\right)$$

Where:

$\alpha =$ reliability coefficient

K =the number of questions of the instrument

S_i^2 =variance of score in each question

S_t^2 =variance of total score of all respondents

Cronbach's alpha was evaluated using the following criteria.

Table 3.14 Criteria of Cronbach's alpha

Cronbach's alpha	**External consistency**
$\alpha \geq 0.9$	Excellent
$0.8 \leq \alpha < 0.9$	Good
$0.7 \leq \alpha < 0.8$	Acceptable
$0.6 \leq \alpha < 0.7$	Questionable
$0.5 \leq \alpha < 0.6$	Poor
$\alpha < 0.5$	Unacceptable

Source: Gliem & Gliem,(2003)

Prior to the formal data collection, the study conducted a pilot survey with a sample size

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of 30 students. Reliability testing was performed, and the Cronbach Alphas were greater than 0.7, indicating the consistency of the items. The Cronbach's alpha of PI was 0.678 at first. After deleting item "Hesitant to try out new M-learning technologies", the reliability has been improved, that is 0.866 as presented in the table. So the final version of the items are 57 items.

Table 3.15 Cronbach's alpha of each latent variable

Latent variable	**PE**	**EE**	**SI**	**FC**	**SE**	**PI**	**CQ**	**BI**	**UB**
Cronbach's alpha	0.881	0.925	0.919	0.899	0.887	0.866	0.922	0.883	0.86

3.7 Data collection

The following procedure was adopted in the data collection process.

Primary data

a. Provide and request the letters of cooperation for collecting data and approved by the authorized person from the Ph.D. Program in Industrial Business Administration, KMITL. The proposal of requested letters is to ask for user information from 630 respondents to collect the data in this research.

b. This study aims to distribute questionnaires to 630 respondents before collecting the data.

c. Compile the 630 questionnaires, and then analyze the data.

Secondary data

d. The data collection consists of concepts, literature, and studies from various sources, for example books, papers, documents, the Internet, government and private sector statistical evidence, and reporting.

3.8 Data analysis

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After the questionnaires were received, the data needs to be preprocessed. This involved the removal of the missing data, checking for the outliers and removing them, and any values, which seem not to align with the rest of the data. Then the data was analyzed to evaluate their validity and reliability. The study applied a level of significance of 5%. The following analysis procedure was adopted:

1. The first analysis was the descriptive statistics. The descriptive statistics involved calculating characteristics of the variables used in the data, for example mean, mode, median, standard deviation, percentiles, skewness, kurtosis, maximum and minimum values. The purpose of conducting the descriptive analysis was to understand the characteristic behavior of the data before engaging in deep statistic analysis.

2. The second analysis was correlation analysis. Pearson's Correlation Analysis was conducted to evaluate the correlation between and among the variables. This was a basic analysis in the structural equation modeling (SEM) analysis of finding factors that influence the behavioral intention to use mobile learning. The correlation analysis consideration criteria are presented in the following table.

Table 3.16 levels of correlation coefficient

Correlation Coefficient (*r*)	**Level of Correlation**
$r \geq 0.8$	Very high
$0.6 \leq r < 0.8$	High
$0.4 \leq r < 0.6$	Moderate
$0.2 \leq r < 0.4$	Low
$r < 0.2$	Very low

Source: Akram, Ajmal & Munirr(2008)

3.KMO is considered appropriate for testing compatibility between empirical data and the conceptual framework for data suitability measurement. The test measures sampling

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adequacy for each variable in the model and the complete model.

4.The conceptual framework has been examined using the AMOS, and also the theories, concepts, and examination of the literature concerned have been obtained.

3.9 Statistical analysis

In this research, the researcher uses the Structural Equation Modeling (SEM), which is a model that combines the principles of statistical analysis of two types together, namely path analysis and factor analysis. Hair et al. (2006) explained that the structural equation model is a multivariate analysis technique which combines the factor analysis and multiple regressions. SEM is used to examine the relationships between variables in the conceptual framework both direct and indirect effects. The most popular statistical program used for SEM model is AMOS.

The AMOS Version 23 is used for analyzing data in this research to:

- Study the relationship between latent variables by theoretical testing.
- Analyze latent variables related to indicators or empirical variables.

3.9.1 Confirmatory Factor Analysis: CFA

By examining the quality of the measurement, the AMOS program increases the opportunity to analyze variance and covariance by applying this technique to confirm factor analysis (Confirmatory Factor Analysis: CFA) to check the harmony, accuracy or consistency of the gauge construction. CFA was first developed by Jöreskog (1969) and has built upon and replaced older methods of analyzing construct validity such as the MTMM Matrix as described in Campbell & Fiske (1959). CFA is a special form of factor analysis, most commonly used in social science research. It is used to test whether measures of a construct are consistent with a researcher's understanding of the nature of that construct. As such, The objective of the technique is to test the hypothesis of the relationship between between exogenous latent variables and endogenous latent variables.

The congruence evaluation between the empirical data and the conceptual framework to be also conducted. The fit indices details are presented in the following table.

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Table 3.17 Evaluation indices of model fitting degree

Statistics	Symbol	Objective	Criteria
Relative Chi-square	X^2/df	prove the conceptual framework and the empirical data is consistent	< 5

Table 3.17 (continue)

Statistics	Symbol	Objective	Criteria
Goodness of Fit Index	GFI	Use the decision coefficient and the regression standard deviation to test the degree of fitting of the model to the sample observations	> 0.9
Comparative Fit Index	CFI	Compare the fit of a target model to the fit of an independent model	> 0.9
Tucker Lewis index	TLI	Measure TLI, between 0 and 1	> 0.9
Root mean square of approximation	RMSEA	Show conceptual framework errors in for of RMSEA, between 0-1	< 0.05
Root Mean Square Residual	RMR	Compare the mean residuals between the predicted correlation and the actual observation correlation to measure the degree of model fitting	< 0.05

Source: Wheaton, Muthen, Alwin & Summers (1977)

3.9.2 The Structural Equation Modeling (SEM)

The structural equation modeling (SEM) was applied to evaluate the main objectives of the study - students' behavioral intention and use of mobile learning by incorporating the Integration of Self-efficacy, Personal Innovativeness and Content Quality to UTAUT. SEM is a quantitative research technique, which is suitable for showing the causal relationships among the study variables. The analysis is usually based on the study hypothesis, evaluating

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the latent variables (effects of independent variables on the dependent variables) guided by the stated hypothesis.

3.10 Ethical Consideration

In this study, ethical consideration was a critical aspect from the start to the end of the research. First, the researcher sought all the relevant and required permission from concerned institutions before collecting the data. The analysis only used data to compile and find the answer. The researcher also ensured that the data collected was only applied for the purpose of the objective stated in this study only. The personal information collected from the respondents was held confidentially and never shared with any other person. All the information collected from the participants was maintained with complete privacy to ensure their dignity and confidentiality. Finally, all participants agreed to participate in this study.

3.11 Conclusion

This chapter has described the methodology that was applied in the research of the study. First, the population and sample size are determined. Then the study used primary data using questionnaire from the representative sample for quantitative research. The primary data was then analyzed using statistical techniques such as correlation analysis and SEM.

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CHAPTER 4

ANALYSIS AND FINDINGS

Based on the extended UTAUT model, this study examines the primary factors influencing behavioral intention and the actual use of mobile learning among Chinese higher vocational students. We incorporated three additional variables—self-efficacy, personal innovativeness, and content quality—to explore the factors affecting mobile learning usage from both personal and quality perspectives.

The chapter is divided into five sections.

1. The first section is a descriptive statistic of the demographic variables used in the data.

2. The second section are the descriptive statistics of the respondents regarding the study variables, including performance expectancy, effort expectancy, social influence, facilitating conditions, self-efficacy, personal innovativeness, content quality, behavioral intention to use and use behavior.

3. The third section presents the test for normality.

4. The fourth section presents the results of the measurement model.

5. The fifth section reports the findings of the Structural Equation Modelling (SEM).

4.1 Descriptive statistics of demographic variables

A total sample of 636 students was selected for the current study. Table presents the demographic characteristics of the sample. According to the statistics, the males were 55.35% and the females were 44.65%. When considering the age, the most students were around 22-23, the least students were over 24. The grade for all the student were 19.5%, 48.27% and 32.23% respectively from freshman year to junior year. Since the development of mobile learning in higher vocational colleges varies across regions, we selected one college from each region using stratified random sampling (Parsons, 2014). The proportion of each region was calculated by dividing the number of higher vocational students in each region by the

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total number of higher vocational students. This figure was then multiplied by the sample size to obtain the sample of each region. The regional distribution of the student sample was generally in line with expectations. In terms of the usage of mobile phone per day, 63.84% of the students spend over two hours. 32.55% of the students spend one to two hours. Only 3.62% of the student spend less than one hour. In terms of mobile learning experience, more than half of the students (56.92%) have over two years mobile learning experience. 0-1 year and 1-2 years are nearly equal.

Table 4.1 Sample characteristics (N=636)

Measure	Item	Frequency	Percentage (%)
Gender	Male	352	55.35%
	Female	284	44.65%
Age	18-19	109	17.14%
	20-21	186	29.25%
	22-23	304	47.80%
	Over 24	37	5.82%
Grade	Freshman year	124	19.50%
	Sophomore year	307	48.27%
	Junior year	205	32.23%
Region	Northeast	43	6.76%
	North	67	10.53%
	Northwest	43	6.76%
	Central	112	17.61%
	East	179	28.14%
	Southwest	98	15.41%
	South	94	14.78%
Use mobile phone for internet per day	Less than 1 hour	23	3.62%
	1-2 hours	207	32.55%
	More than 2 hours	406	63.84%

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Table 4.1 (continue)

Measure	Item	Frequency	Percentage (%)
Mobile learning experience	0-1year	134	21.07%
	1-2 years	140	22.01%
	2 years and more	362	56.92%

4.2 Descriptive statistics of respondents regarding latent variables

This section analyzes the feedback of the respondents regarding the various latent variables, and their observed variables. There were nine latent variables used in this study.

4.2.1 Performance expectancy

Performance expectancy was evaluated using three observed variables, perceived usefulness, relative advantage, and outcome expectation. All the items of the perceived usefulness were around a mean of 3.64 and a standard deviation of 1.22. The highest respondents' view of relative advantage was "Using the M-learning increases my productivity" (mean of 3.76), followed by "Using M-learning system increases the quality of learning process" (mean of 3.71). The overall outcome expectancy mean was 3.70 and the overall outcome expectancy standard deviation was 1.2. In total, the mean and standard deviation was 3.68 and 1.2 respectively.

Table 4.2 Performance expectancy respondents opinions

Performance expectancy		**0pinion level**					**Mean**	**Std. Dev**	**Level**
		1	**2**	**3**	**4**	**5**			
		Frequency (n) and Percentages (%)							
Perceived Usefulness							**3.64**	**1.22**	**Agree**
I would find M-learning useful in my learning.	n	51	60	131	206	188	**3.66**	1.22	Agree
	%	8.0	9.4	20.6	32.4	29.6			

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Table 4.2 (continue)

Performance expectancy		0pinion level					Mean	Std. Dev	Level
		1	2	3	4	5			
		Frequency (n) and Percentages (%)							
Using M-learning would make it easier for my learning.	n	56	61	132	192	195	**3.64**	1.25	Agree
	%	8.8	9.6	20.8	30.2	30.7			
Using M-learning would improve my learning performance.	n	46	64	147	201	178	**3.63**	1.20	Agree
	%	7.2	10.1	23.1	31.6	28.0			
Relative Advantage							**3.71**	**1.19**	**Agree**
Using the M-learning enables me to accomplish tasks more quickly.	n	57	50	123	233	173	**3.65**	1.21	Agree
	%	9.0	7.9	19.3	36.6	27.2			
Using the M-learning increases my productivity.	n	40	60	120	208	208	**3.76**	1.18	Agree
	%	6.3	9.4	18.9	32.7	32.7			
Using M-learning system increases the quality of learning process.	n	44	49	144	210	189	**3.71**	1.17	Agree
	%	6.9	7.7	22.6	33.0	29.7			
Outcome Expectation							**3.70**	**1.20**	**Agree**
Using a M-learning platform increases my chances of learning things that are important to me.	n	42	56	135	213	190	**3.71**	1.17	Agree
	%	6.6	8.8	21.2	33.5	29.9			
If I use M-learning, my classmates will perceive me as competent.	n	49	59	129	213	186	**3.67**	1.21	Agree
	%	7.7	9.3	20.3	33.5	29.2			

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Table 4.2 (continue)

Performance expectancy		0pinion level					Mean	Std. Dev	Level
		1	2	3	4	5			
		Frequency (n) and Percentages (%)							
Using M-learning will increase my chances of getting a better grade.	n	47	56	136	190	207	**3.71**	1.22	Agree
	%	7.4	8.8	21.4	29.9	32.5			
Overall							**3.68**	**1.20**	**Agree**

4.2.2 Effort expectancy

Effort expectancy had two observed variables, perceived ease of use and ease of use. The highest-ranked item of perceived ease of use was "I would find M-learning easy to use" with the mean of 3.65, and the standard deviation of 1.23. As for ease of use, the two items "Overall, I believe that M-learning is easy to use", "I find it easy to get M-learning to do what I want it to do" ranked much higher than the last one "Learning to operate M-learning is easy for me". Overall, the mean and standard deviation of effort expectancy was 3.6 and 1.24 respectively.

Table 4.3 Effort expectancy respondents opinions

Effort expectancy		0pinion level					Mean	Std. Dev	Level
		1	2	3	4	5			
		Frequency (n) and Percentages (%)							
Perceived Ease of Use							**3.62**	**1.23**	**Agree**
My interaction with M-learning would be clear and understandable.	n	6	156	110	181	183	**3.60**	1.17	Agree
	%	0.9	24.5	17.3	28.5	28.8			
It would be easy for me to become skillful at using the M-learning.	n	67	60	119	207	183	**3.60**	1.28	Agree
	%	10.5	9.4	18.7	32.5	28.8			

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Table 4.3 (continue)

Effort expectancy		0pinion level					Mean	Std. Dev	Level
		1	2	3	4	5			
		Frequency (n) and Percentages (%)							
I would find M-learning easy to use.	n	54	66	106	230	180	**3.65**	1.23	Agree
	%	8.5	10.4	16.7	36.2	28.3			
Ease of Use							**3.59**	**1.26**	**Agree**
Learning to operate M-learning is easy for me.	n	35	139	95	189	178	**3.53**	1.26	Agree
	%	5.5	21.9	14.9	29.7	28.0			
I find it easy to get M-learning to do what I want it to do.	n	57	63	129	205	182	**3.62**	1.24	Agree
	%	9.0	9.9	20.3	32.2	28.6			
Overall, I believe that M-learning is easy to use.	n	66	61	103	218	188	**3.63**	1.28	Agree
	%	10.4	9.6	16.2	34.3	29.6			
Overall							**3.60**	**1.24**	**Agree**

4.2.3 Social influence

Social influence was evaluated using two observed variables, subjective norm and social factors. The three opinions of subjective norm got similar mean with different variances. The highest-ranked opinion of social factors was "The lecturers and other staff at my college are helpful in the use of M-learning" with a mean of 3.82 and a standard deviation of 1.17. In general, the mean and standard deviation of social influence was 3.77 and 1.16.

Table 4.4 Social influence respondents opinions

Social influence	0pinion level					Mean	Std. Dev	Level
	1	2	3	4	5			
	Frequency (n) and Percentages (%)							

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Subjective Norm							**3.77**	**1.15**	**Agree**
People who influence my behaviour think that I should use M-learning.	n	40	45	135	217	199	**3.77**	1.15	Agree
	%	6.3	7.1	21.2	34.1	31.3			
People who are important to me think that I should use M-learning.	n	43	47	117	234	195	**3.77**	1.16	Agree
	%	6.8	7.4	18.4	36.8	30.7			
My classmates and teachers think that I should use M-learning.	n	36	50	139	220	191	**3.75**	1.13	Agree
	%	5.7	7.9	21.9	34.6	30.0			
Social Factors							**3.77**	**1.18**	**Agree**
The lecturers and other staff at my college are helpful in the use of M-learning.	n	45	38	122	214	217	**3.82**	1.17	Agree
	%	7.1	6.0	19.2	33.6	34.1			
I use M-learning because of the proportion of classmates who use M-learning.	n	47	51	121	215	202	**3.75**	1.20	Agree
	%	7.4	8.0	19.0	33.8	31.8			
In general, my college has supported the use of M-learning.	n	42	58	114	235	187	**3.73**	1.17	Agree
	%	6.6	9.1	17.9	36.9	29.4			
Overall							**3.77**	**1.16**	**Agree**

4.2.4 Facilitating conditions

Facilitating conditions had two observed variables including perceived behavioral control and facilitating conditions. The highest-ranked sense of perceived behavioral control was “I have the resources necessary to use M-learning system” with a mean of 3.8 and a

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standard deviation of 1.14, followed by "I have the knowledge necessary to use M-learning system" (mean of 3.73). The overall mean and standard deviation of the second observed variable facilitating conditions was 3.72 and 1.19.

Table 4.5 Facilitating conditions respondents opinions

Facilitating conditions	0pinion level					Mean	Std. Dev	Level
	1	2	3	4	5			
	Frequency (n) and Percentages (%)							
Perceived Behavioral Control						**3.75**	**1.19**	**Agree**
I have the resources necessary to use M-learning system.	n 13	104	96	206	217	**3.80**	1.14	Agree
	% 2.0	16.4	15.1	32.4	34.1			
I have the knowledge necessary to use M-learning system.	n 44	45	134	230	183	**3.73**	1.15	Agree
	% 6.9	7.1	21.1	36.2	28.8			
M-learning is compatible with other systems I use.	n 59	59	101	204	213	**3.71**	1.27	Agree
	% 9.3	9.3	15.9	32.1	33.5			
Facilitating conditions						**3.72**	**1.19**	**Agree**
There is a specific person or group available for assistance with any technical problem I may encounter.	n 50	51	125	204	206	**3.73**	1.22	Agree
	% 7.9	8.0	19.7	32.1	32.4			
Specialized instruction concerning M-learning was available to me.	n 50	45	136	216	189	**3.71**	1.19	Agree
	% 7.9	7.1	21.4	34.0	29.7			

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Table 4.5 (continue)

Facilitating conditions		0pinion level					Mean	Std. Dev	Level
		1	2	3	4	5			
		Frequency (n) and Percentages (%)							
Using M-learning fits my learning style.	n	41	49	133	226	187	**3.74**	1.15	Agree
	%	6.4	7.7	20.9	35.5	29.4			
Overall							**3.74**	**1.19**	**Agree**

4.2.5 Self-efficacy

Self-efficacy was evaluated with two observed variables, confidence and capability. With regard to confidence, the highest-ranked opinion was "I am confident of using the M-learning even if I have never used such a system before" (mean of 3.72), followed by "I am confident of using the mobile learning even if I have only the online instructions for reference" (mean of 3.64). The overall mean and standard deviation of capability was 3.7 and 1.19.

Table 4.6 Self-efficacy respondents opinions

Self-efficacy		0pinion level					Mean	Std. Dev	Level
		1	2	3	4	5			
		Frequency (n) and Percentages (%)							
Confidence							**3.65**	**1.24**	**Agree**
I am confident of using the M-learning even if there is no one around to show me how to do it.	n	45	119	75	208	189	**3.59**	1.28	Agree
	%	7.1	18.7	11.8	32.7	29.7			
I am confident of using the M-learning even if I have never used such a system before.	n	54	54	110	217	201	**3.72**	1.23	Agree
	%	8.5	8.5	17.3	34.1	31.6			

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Table 4.6 (continue)

Self-efficacy		0pinion level					Mean	Std. Dev	Level
		1	2	3	4	5			
		Frequency (n) and Percentages (%)							
I am confident of using the mobile learning even if I have only the online instructions for reference.	n	47	67	133	212	177	**3.64**	1.20	Agree
	%	7.4	10.5	20.9	33.3	27.8			
Capability							**3.70**	**1.19**	**Agree**
I have the ability to use all mobile-learning technology features	n	53	61	106	209	207	**3.72**	1.24	Agree
	%	8.3	9.6	16.7	32.9	32.5			
I have the ability to post comments and respond to comments posted via mobile learning.	n	6	125	125	199	181	**3.67**	1.11	Agree
	%	0.9	19.7	19.7	31.3	28.5			
I have the ability to locate information on the course website using mobile learning.	n	46	61	118	217	194	**3.71**	1.20	Agree
	%	7.2	9.6	18.6	34.1	30.5			
Overall							**3.67**	**1.21**	**Agree**

4.2.6 Personal innovativeness

Personal innovativeness had two observed variables, behaviors and states. The highest-ranked sense of behaviors was “If I heard about a new M-learning technology, I look for ways to experiment with it” with a mean of 3.61 and standard deviation of 1.25, followed by “I like to experiment new M-learning technologies” with a mean of 3.56 and standard

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deviation of 1.28. The overall mean and standard deviation of states was 3.56 and 1.31 respectively.

Table 4.7 Personal innovativeness respondents opinions

Personal innovativeness		0pinion level					Mean	Std. Dev	Level
		1	2	3	4	5			
		Frequency (n) and Percentages (%)							
Behaviors							**3.58**	**1.27**	**Agree**
I like to experiment new M-learning technologies.	n	71	57	129	205	174	**3.56**	1.28	Agree
	%	11.2	9.0	20.3	32.2	27.4			
If I heard about a new M-learning technology, I look for ways to experiment with it.	n	61	63	116	221	175	**3.61**	1.25	Agree
	%	9.6	9.9	18.2	34.7	27.5			
States							**3.56**	**1.31**	**Agree**
Among my peers, I am usually the first to try out new M-learning technology.	n	78	60	123	179	196	**3.56**	1.34	Agree
	%	12.3	9.4	19.3	28.1	30.8			
I am interested in M-learning technologies that are new to me.	n	68	56	144	188	180	**3.56**	1.28	Agree
	%	10.7	8.8	22.6	29.6	28.3			
Overall							**3.57**	**1.29**	**Agree**

4.2.7 Content quality

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Content quality had two observed variables, informativeness and accessibility. With regard to informativeness, the mean and standard deviation was 3.83 and 1.13 respectively. The highest-ranked opinion of accessibility was “Mobile learning application provides timely content” (mean of 3.83) and “ It is easy to find the information that I need when using M-learning” (mean of 3.82), followed by “The content of the course provided by M-learning is easy to understand” (mean of 3.79) and “The course content of mobile learning is more vivid than that of traditional classroom” (mean of 3.78). In general, the mean and standard deviation of content quality was 3.81 and 1.16 respectively.

Table 4.8 Content quality respondents opinions

Content quality		**0pinion level**					**Mean**	**Std. Dev**	**Level**
		1	**2**	**3**	**4**	**5**			
		Frequency (n) and Percentages (%)							
Informativeness							**3.83**	**1.13**	**Agree**
Mobile learning application provides accurate content.	n	0	103	104	218	211	**3.84**	1.06	Agree
	%	0.0	16.2	16.4	34.3	33.2			
Mobile learning application provides up to date content.	n	41	40	140	183	232	**3.83**	1.18	Agree
	%	6.4	6.3	22.0	28.8	36.5			
Mobile learning application provides up to date content. ides content that is relevant to my needs.	n	40	45	126	212	213	**3.81**	1.16	Agree
	%	6.3	7.1	19.8	33.3	33.5			
Accessibility							**3.80**	**1.18**	**Agree**
The content of the course provided by M-learning is easy to understand.	n	36	75	99	204	222	**3.79**	1.20	Agree
	%	5.7	11.8	15.6	32.1	34.9			

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Table 4.8 (continue)

Content quality		0pinion level					Mean	Std. Dev	Level
		1	2	3	4	5			
		Frequency (n) and Percentages (%)							
Mobile learning application provides timely content.	n	48	32	112	232	212	**3.83**	1.17	Agree
	%	7.5	5.0	17.6	36.5	33.3			
It is easy to find the information that I need when using M-learning.	n	38	51	114	219	214	**3.82**	1.16	Agree
	%	6.0	8.0	17.9	34.4	33.6			
The course content of mobile learning is more vivid than that of traditional classroom.	n	46	44	119	220	207	**3.78**	1.18	Agree
	%	7.2	6.9	18.7	34.6	32.5			
Overall							**3.81**	**1.16**	**Agree**

4.2.8 Behavioral intention

Behavioral intention was evaluated using three observed variables, intention to use, predicting to use and planning to use. Each observed variable had only one item. The highest-ranked item was “I predict I would use M-learning in the future” with a mean of 3.76, followed by “I intend to use M-learning in the future” (mean of 3.74) and “I plan to use M-learning in the future” (mean of 3.71). The overall mean and standard deviation of behavioral intention was 3.74 and 1.24.

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Table 4.9 Behavioral intention respondents opinions

Behavioral intention	0pinion level					Mean	Std. Dev	Level
	1	2	3	4	5			
	Frequency (n) and Percentages (%)							
Intention to use						**3.74**	**1.26**	**Agree**
I intend to use M-learning in the future.	n 56	53	114	189	224	**3.74**	1.26	Agree
	% 8.8	8.3	17.9	29.7	35.2			
Predicting to use						**3.76**	**1.23**	**Agree**
I predict I would use M-learning in the future.	n 50	57	102	215	212	**3.76**	1.23	Agree
	% 7.9	9.0	16.0	33.8	33.3			
Planning to use						**3.71**	**1.22**	**Agree**
I plan to use M-learning in the future.	n 56	50	104	236	190	**3.71**	1.22	Agree
	% 8.8	7.9	16.4	37.1	29.9			
Overall						**3.74**	**1.24**	**Agree**

4.2.9 Use behavior

Use behavior has three observed variables, preference, frequently use and recommendations. The mean of preference was 3.62 and the standard deviation of preference was 1.24. The mean of frequently use was 3.6 and the standard deviation of frequently use was 1.25. The mean of recommendations was 3.58 and the standard deviation of recommendations was 1.24.

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Table 4.10 Use behavior respondents opinions

Use behavior		0pinion level					Mean	Std. Dev	Level
		1	2	3	4	5			
		Frequency (n) and Percentages (%)							
Preference							**3.62**	**1.24**	**Agree**
I prefer to use M-learning when available.	n	59	58	134	199	186	**3.62**	1.25	Agree
	%	9.3	9.1	21.1	31.3	29.2			
I aim to use M-learning instead of traditional ones.	n	61	51	124	232	168	**3.62**	1.23	Agree
	%	9.6	8.0	19.5	36.5	26.4			
Frequently use							**3.60**	**1.25**	**Agree**
I use M-learning daily.	n	66	58	127	202	183	**3.59**	1.27	Agree
	%	10.4	9.1	20.0	31.8	28.8			
I use M-learning sometimes.	n	56	56	144	205	175	**3.61**	1.22	Agree
	%	8.8	8.8	22.6	32.2	27.5			
I will use M-learning daily in the future.	n	55	66	139	190	186	**3.61**	1.25	Agree
	%	8.6	10.4	21.9	29.9	29.2			
Recommendations							**3.58**	**1.24**	**Agree**
I recommend M-learning for others to use.	n	64	51	142	211	168	**3.58**	1.24	Agree
	%	10.1	8.0	22.3	33.2	26.4			
Overall							**3.61**	**1.24**	**Agree**

4.3 Test for normality

This section evaluated whether the latent variables were normally distributed. There were nine latent variables measured by different observed variables. The variables were:

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performance expectancy measured by three variables (perceived usefulness , relative advantage, and outcome expectation); effort expectancy measured by two observed variables (perceived ease of use, ease of use) ; social influence measured by two variables(subjective norm and social factors), facilitating condition measured by two observed variables (perceived behavioral control and facilitating condition); self-efficacy measured by two observed variables (confidence and capability); personal innovativeness measured by two observed variables (behaviors and states); content quality measured by two observed variables (informativeness and accessibility); behavioral intention measured by three observed variables (Intention to use, prediction to use and planning to use); use behavior measured by three observed variables (preference, frequently use and recommendations). The average skewness and kurtosis for each observed variable and the latent variables are presented in Table 4.11 below.

Table 4.11 Test for normality

Latent variable	**Skewness**	**Kurtosis**	**Normal distribution**
Performance expectancy	-0.725	-0.334	pass
Effort expectancy	-0.595	-0.701	pass
Social influence	-0.837	-0.044	pass
Facilitating conditions	-0.778	-0.245	pass
Self-efficacy	-0.670	-0.537	pass
Personal innovativeness	-0.655	-0.609	pass
Content quality	-0.836	-0.105	pass
Behavioral intention	-0.841	-0.243	pass
Use behavior	-0.683	-0.463	pass

Performance expectancy was measured by three variables. Skewness is -0.67, -0.77 and -0.73 respectively, and kurtosis is -0.45, -0.22 and -0.32 respectively. Effort Expectancy was measured by two variables. Skewness is -0.58 and -0.6 while kurtosis is -0.7 and -0.71 respectively. Social influence was measured by two variables. Skewness is -0.82 and -0.85,

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while kurtosis is -0.02 and -0.07 respectively. Facilitating conditions was measured by two variables. Skewness is -0.76 and -0.8, while kurtosis is -0.33 and -0.15 respectively. Self-efficacy was measured by two observed variables. Skewness is -0.68 and -0.65 while kurtosis is -0.56 and -0.53 respectively. Personal innovativeness was measured by two observed variables. Skewness is -0.69 and -0.63 while kurtosis is -0.53 and -0.68 respectively. Content quality was measured by two observed variables. Skewness is -0.76 and -0.8 while kurtosis is -0.26 and -0.03 respectively. Behavioral intention was measured by three variables. Skewness is -0.80, -0.85 and -0.86 while kurtosis is -0.36, -0.23 and -0.15 respectively. Use behavior was measured by three variables. Skewness is -0.72, -0.66 and -0.68 while kurtosis is -0.39, -0.51 and -0.46 respectively.

Distribution is considered acceptable within a normal range when indicators of the skewness and kurtosis values are less than 2 and 3 respectively(Azzalini 2005; Hair et al. 2006). The results above for skewness and kurtosis satisfy the normality assumption because all the variables skewness is not above 1, and kurtosis is not above 1.5. Since the data satisfied normality test, it was considered suitable to be used in carrying out the Structural Equation Model Analysis (SEM).

4.4 Results of the measurement model

This section contains reliability and validity tests. This study used SPSS 27.0 to implement the reliability test. Amos 23 was used to conduct the confirmatory factor analysis (CFA). Cronbach Alpha was performed to evaluate the reliability of the measurement. CFA was tested to show how well the measurement fit the proposed model. In specific, the following indicators of measurement fitting were adopted: χ^2/df, CFI, GFI, TLI, RMSEA and RMR. Factor loading, composite reliability (CR) and average variance extracted (AVE) were the indicators of convergent validity and discriminant validity.

4.4.1 First order CFA

This section obtained factor loadings for each item independently. The factor loading should be significant and greater than 0.6 (Hulland, 1999).

CFA--Performance Expectancy

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There are ten items in performance expectancy including three observed variables at first. The study used CFA to get the factor loadings of each item and found that the loading of item PE_PU4 was 0.497 which was less than 0.6 , so this item was removed. Then we recalculated the factor loadings and obtained the following results. The factor loadings were statistically significant. The factor loadings were from 0.7 to 0.77. GFI=0.988, CFI=0.999, NFI=0.989.

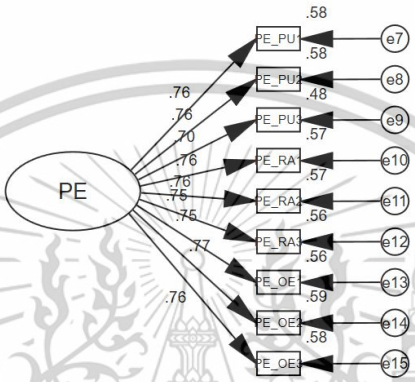

Figure 4.1 CFA--Performance Expectancy

CFA--Effort Expectancy

There are seven items in effort expectancy including two observed variables at first. The study used CFA to get the factor loadings of each item and found that the loading of item EE_EU3 was 0.524 which was less than 0.6, so this item was removed. Then we recalculated the factor loadings and obtained the following results. The factor loadings were statistically significant. The factor loadings were from 0.77 to 0.88. GFI=0.988, CFI=0.999, NFI=0.989.

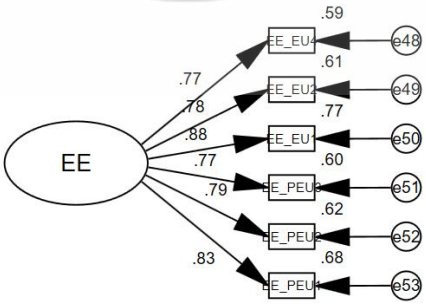

Figure 4.2 CFA--Effort Expectancy

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CFA--Social Influence

There are six items in social influence including two observed variables. The study used CFA to get the factor loadings of each item and found that the loading of all items passed the criteria. The factor loadings were statistically significant as Figure 4.3. The factor loadings were from 0.7 to 0.77. GFI=0.996, CFI=1, NFI=0.996.

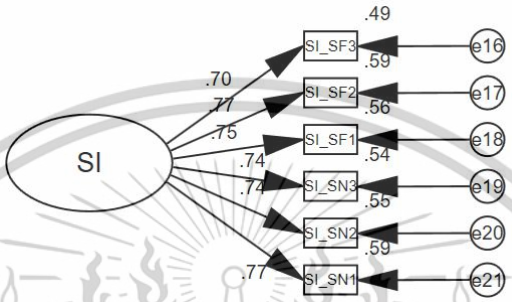

Figure 4.3 CFA--Social Influence

CFA--Facilitating Conditions

There are seven items in facilitating conditions including two observed variables at first. The study used CFA to get the factor loadings of each item and found that the loading of item FC_FC4 was 0.457 which was less than 0.6, so this item was removed. Then we recalculated the factor loadings and obtained the following results. The factor loadings were statistically significant. The factor loadings were from 0.68 to 0.8. GFI=0.991, CFI=0.995, NFI=0.990.

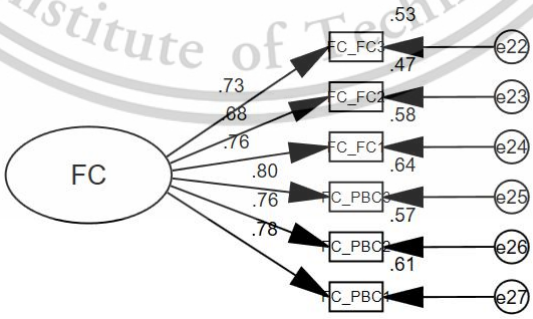

Figure 4.4 CFA--Facilitating Conditions

CFA--Self-Efficacy

There are six items in self-efficacy including two observed variables. The study used

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CFA to get the factor loadings of each item and found that the loading of all items passed the criteria. The factor loadings were statistically significant as Figure 4.5. The factor loadings were from 0.76 to 0.91. GFI=0.991, CFI=0.995, NFI=0.991.

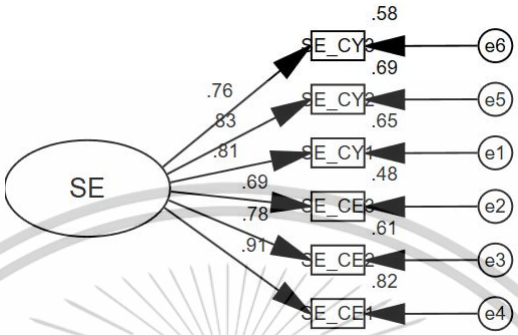

Figure 4.5 CFA--Self-Efficacy

CFA--Personal Innovativeness

There are six items in personal innovativeness including two observed variables. The study used CFA to get the factor loadings of each item and found that the loading of all items passed the criteria. The factor loadings were statistically significant as Figure 4.6. The factor loadings were from 0.69 to 0.74. GFI=0.998, CFI=1, NFI=0.997.

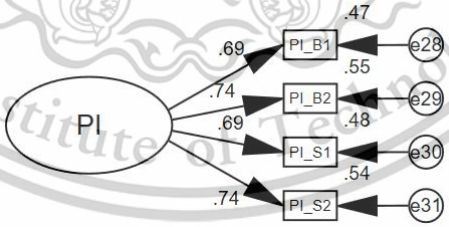

Figure 4.6 CFA--Personal Innovativeness

CFA--Content Quality

There are eight items in content quality including two observed variables at first. The study used CFA to get the factor loadings of each item and found that the loading of item CQ_A5 was 0.542 which was less than 0.6, so this item was removed. Then we recalculated the factor loadings and obtained the following results. The factor loadings were statistically

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significant. The factor loadings were from 0.73 to 0.84. GFI=0.993, CFI=0.999, NFI=0.994.

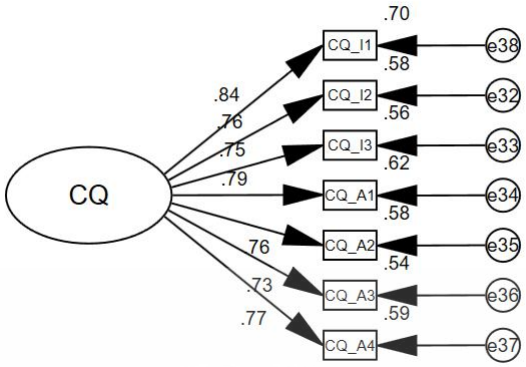

Figure 4.7 CFA--Content Quality

CFA--Behavioral Intention

There are three items in behavioral intention corresponding to three observed variables. The study used CFA to get the factor loadings of each item and found that the loading of all items passed the criteria. The factor loadings were statistically significant as Figure 4.8. The factor loadings were from 0.78 to 0.83. GFI=1, CFI=1, NFI=1

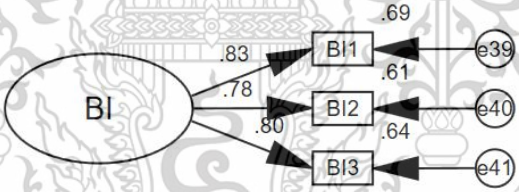

Figure 4.8 CFA--Behavioral Intention

CFA--Use Behavior

There are six items in use behavior including three observed variables. The study used CFA to get the factor loadings of each item and found that the loading of all items passed the criteria. The factor loadings were statistically significant as Figure 4.9. The factor loadings were from 0.75 to 0.78. GFI=0.997, CFI=0.997, NFI=0.997

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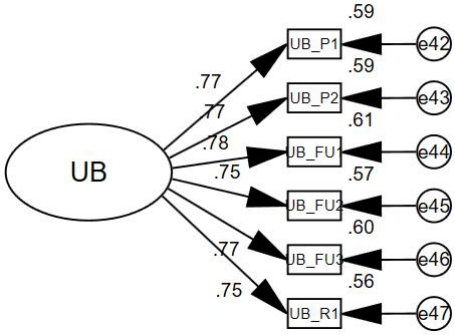

Figure 4.9 CFA--Use Behavior

4.4.2 Validity test

Model fit

The validity of the model is tested by CFA, including goodness of fit, convergence validity and discriminant validity. CFA is used to test whether measures of a construct are consistent with a researcher's understanding of the nature of that construct shown in Figure 4.10. The evaluation of consistency between empirical data and conceptual framework is reflected by goodness of fit. The goodness-of-fit indexes were listed in the Table 4.12 . All the indicators satisfied the criteria.

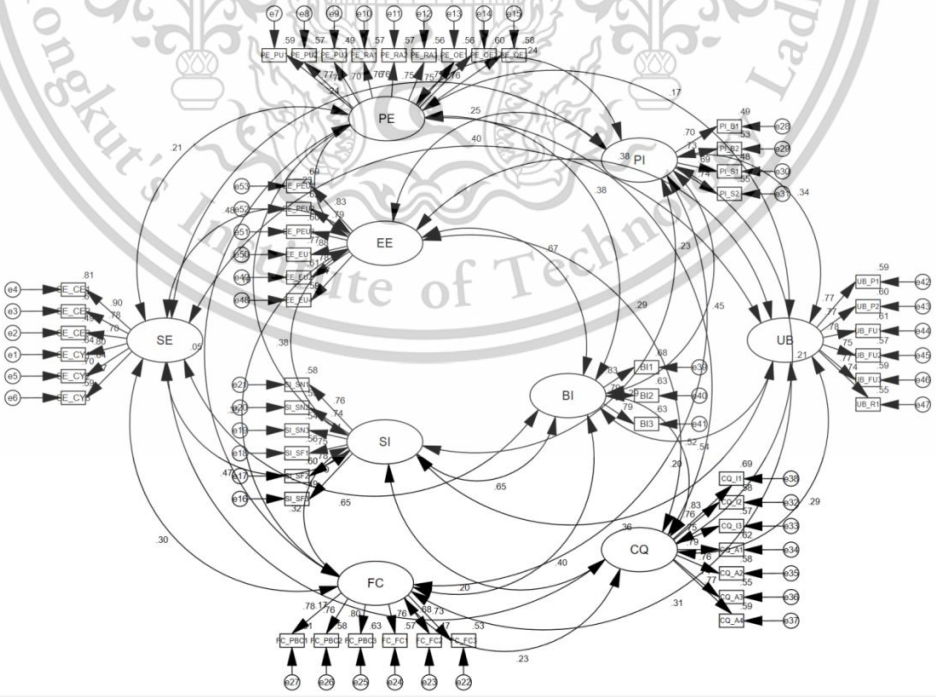

Figure 4.10 CFA results

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Table 4.12 Measurement model fit indices

Indices	Criteria	Statistic value
X^2/df	< 5	1.229
GFI	> 0.9	0.917
CFI	> 0.9	0.985
NFI	> 0.9	0.923
TLI	> 0.9	0.984
RMSEA	< 0.05	0.019
RMR	< 0.05	0.045

It can be seen that the measurement model proved to have a good fit to the data. The X^2/df = 1.229 (considered good since it was below 5 and was being influenced by sample size) (Schumacker & Lomax, 2004). GFI was 0.917; CFI was 0.985; NFI was 0.923; TLI was 0.984; which provided an excellent fit, since the values were greater than 0.9. Additionally, the RMSEA is 0.010(below the threshold of 0.50) (Schumacker & Lomax, 2010). The results of the CFA indicated that it was feasible to move on and conduct the Structural Equation Modeling.

Convergence validity--Factor loadings of latent variables

Convergence validity requires that there is a strong correlation under the same latent variable. The measurement criteria are (1) factor loading is significant and greater than 0.6 (Hulland, 1999), (2) CR > 0.7, (3) AVE > 0.5.

Table 4.13 Results for factor loadings of Performance Expectancy

Construct	Standardized factor loadings (>0.60)	Squared Multiple Correlations (>0.36)	p-value
PE_PU1	0.765	0.585	***
PE_PU2	0.759	0.574	***
PE_PU3	0.697	0.485	***
PE_RA1	0.756	0.571	***

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Table 4.13 (continue)

Construct	Standardized factor loadings (>0.60)	Squared Multiple Correlations (>0.36)	p-value
PE_RA2	0.757	0.574	***
PE_RA3	0.748	0.559	***
PE_OE1	0.749	0.561	***
PE_OE2	0.772	0.596	***
PE_OE3	0.762	0.583	***

As shown in above table, PE_OE2 was found to have the highest factor loading score of 0.772 and a square multiple correlation of 0.596, which explained approximately 60% of performance expectancy variation. It was followed by PE_PU1, having a factor loading score of 0.765 and a square multiple correlation of 0.585, which explained approximately 59% of performance expectancy variation, The lowest factor loading was PE_PU3 which had a factor loading score of 0.697 with a squared multiple correlations of 0.485, accounting for 49% variation in PE.

Table 4.14 Results for factor loadings of Effort Expectancy

Construct	Standardized factor loadings (>0.60)	Squared Multiple Correlations (>0.36)	p-value
EE_PEU1	0.831	0.691	***
EE_PEU2	0.788	0.621	***
EE_PEU3	0.773	0.6	***
EE_EU1	0.878	0.769	***
EE_EU2	0.778	0.609	***
EE_EU4	0.767	0.587	***

As shown in above table, EE_EU1 was found to have the highest factor loading score of 0.878 and a square multiple correlation of 0.769, which explained approximately 77% of

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effort expectancy variation. It was followed by EE_PEU, having a factor loading score of 0.831 and a square multiple correlation of 0.691, which explained approximately 69% of effort expectancy variation, The lowest factor loading was EE_EU4 which had a factor loading score of 0.767 with a squared multiple correlations of 0.587, accounting for 59% variation in effort expectancy.

Table 4.15 Results for factor loadings of Social Influence

Construct	Standardized factor loadings (>0.60)	Squared Multiple Correlations (>0.36)	p-value
SI_SN1	0.76	0.577	***
SI_SN2	0.743	0.553	***
SI_SN3	0.734	0.541	***
SI_SF1	0.751	0.563	***
SI_SF2	0.777	0.602	***
SI_SF3	0.702	0.494	***

As shown in above table, SI_SF2 was found to have the highest factor loading score of 0.777 and a square multiple correlation of 0.602, which explained approximately 60% of social influence variation. It was followed by SI_SN1, having a factor loading score of 0.76 and a square multiple correlation of 0.577, which explained approximately 58% of social influence variation, The lowest factor loading was SI_SF3 which had a factor loading score of 0.702 with a squared multiple correlations of 0.494, accounting for 49% variation in social influence.

Table 4.16 Results for factor loadings of Facilitating Conditions

Construct	Standardized factor loadings (>0.60)	Squared Multiple Correlations (>0.36)	p-value
FC_PBC1	0.78	0.608	***
FC_PBC2	0.759	0.575	***

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Table 4.16 (continue)

Construct	Standardized factor loadings (>0.60)	Squared Multiple Correlations (>0.36)	p-value
FC_PBC3	0.799	0.635	***
FC_FC1	0.756	0.573	***
FC_FC2	0.684	0.465	***
FC_FC3	0.728	0.535	***

As shown in above table, FC_PBC3 was found to have the highest factor loading score of 0.799and a square multiple correlation of 0.635, which explained approximately 64% of facilitating conditions variation. It was followed by FC_PBC1, having a factor loading score of 0.78 and a square multiple correlation of 0.608, which explained approximately 61% of facilitating conditions variation, The lowest factor loading was FC_FC2 which had a factor loading score of 0.684 with a squared multiple correlations of 0.465, accounting for 47% variation in facilitating conditions.

Table 4.17 Results for factor loadings of Self-Efficacy

Construct	Standardized factor loadings (>0.60)	Squared Multiple Correlations (>0.36)	p-value
SE_CE1	0.898	0.814	***
SE_CE2	0.781	0.612	***
SE_CE3	0.697	0.486	***
SE_CY1	0.8	0.644	***
SE_CY2	0.837	0.699	***
SE_CY3	0.767	0.588	***

As shown in above table, SE_CE1 was found to have the highest factor loading score of

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0.898and a square multiple correlation of 0.814, which explained approximately 81% of self-efficacy variation. It was followed by SE_CY2, having a factor loading score of 0.837and a square multiple correlation of 0.699, which explained approximately 61% of self-efficacy variation, The lowest factor loading was SE_CE3 which had a factor loading score of 0.697 with a squared multiple correlations of 0.486, accounting for 49% variation in self-efficacy.

Table 4.18 Results for factor loadings of Personal Innovativeness

Construct	Standardized factor loadings (>0.60)	Squared Multiple Correlations (>0.36)	p-value
PI_B1	0.701	0.489	***
PI_B2	0.725	0.529	***
PI_S1	0.694	0.482	***
PI_S2	0.74	0.547	***

As shown in above table, PI_S2 was found to have the highest factor loading score of 0.74 and a square multiple correlation of 0.547, which explained approximately 55% of personal innovativeness variation. It was followed by PI_B2, having a factor loading score of 0.725 and a square multiple correlation of 0.529, which explained approximately 53% of personal innovativeness variation, The lowest factor loading was PI_S1 which had a factor loading score of 0.694 with a squared multiple correlations of 0.482, accounting for 48% variation in personal innovativeness.

Table 4.19 Results for factor loadings of Content Quality

Construct	Standardized factor loadings (>0.60)	Squared Multiple Correlations (>0.36)	p-value
CQ_I1	0.832	0.691	***
CQ_I2	0.761	0.582	***
CQ_I3	0.757	0.567	***
CQ_A1	0.791	0.618	***

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Table 4.19 (continue)

Construct	Standardized factor loadings (>0.60)	Squared Multiple Correlations (>0.36)	p-value
CQ_A2	0.758	0.581	***
CQ_A3	0.737	0.546	***
CQ_A4	0.763	0.589	***

As shown in above table, CQ_I1 was found to have the highest factor loading score of 0.832 and a square multiple correlation of 0.691, which explained approximately 69% of content quality variation. It was followed by CQ_A1, having a factor loading score of 0.791 and a square multiple correlation of 0.618, which explained approximately 62% of content quality variation, The lowest factor loading was CQ_A3 which had a factor loading score of 0.737with a squared multiple correlations of 0.546, accounting for 55% variation in content quality.

Table 4.20 Results for factor loadings of Behavioral Intention

Construct	Standardized factor loadings (>0.60)	Squared Multiple Correlations (>0.36)	p-value
BI1	0.808	0.681	***
BI2	0.772	0.625	***
BI3	0.776	0.631	***

As shown in above table, BI1 was found to have the highest factor loading score of 0.808 and a square multiple correlation of 0.681, which explained approximately 68% of behavioral intention variation. It was followed by BI3, having a factor loading score of 0.776 and a square multiple correlation of 0.631, which explained approximately 63% of behavioral intention variation, The lowest factor loading was BI2 which had a factor loading score of 0.772 with a squared multiple correlations of 0.625, accounting for 63% variation in

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behavioral intention.

Table 4.21 Results for factor loadings of Use Behavior

Construct	Standardized factor loadings (>0.60)	Squared Multiple Correlations (>0.36)	p-value
UB_P1	0.762	0.588	***
UB_P2	0.767	0.596	***
UB_FU1	0.778	0.611	***
UB_FU2	0.747	0.566	***
UB_FU3	0.765	0.592	***
UB_R1	0.738	0.552	***

As shown in above table, UB_FU1 was found to have the highest factor loading score of 0.778 and a square multiple correlation of 0.611, which explained approximately 62% of use behavior variation. It was followed by UB_P2, having a factor loading score of 0.767 and a square multiple correlation of 0.596, which explained approximately 60% of use behavior variation, The lowest factor loading was UB_R1 which had a factor loading score of 0.738 with a squared multiple correlations of 0.552, accounting for 55% variation in use behavior.

Convergence validity--CR and AVE

Internal consistency is a common way to represent consistency and stability, which are referred to as reliability. Cronbach's alpha is used to measure the factor internal reliability of the latent variable, and all the results were higher than the suggested threshold (>0.7) shown in Table 4.22.

Table 4.22 the Results of Cronbach's alpha, CR and AVE

Construct	**Cronbach's alpha (>0.70)**	**CR (>0.70)**	**AVE (>0.50)**
Performance Expectancy	0.917	0.921	0.565

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Table 4.22 (continue)

Construct	Cronbach's alpha (>0.70)	CR (>0.70)	AVE (>0.50)
Effort Expectancy	0.877	0.916	0.646
Social Influence	0.882	0.882	0.555
Facilitating Conditions	0.875	0.886	0.565
Self-efficacy	0.912	0.913	0.639
Personal Innovativeness	0.806	0.807	0.512
Content quality	0.906	0.912	0.596
Behavioral Intention	0.845	0.829	0.617
Use behavior	0.894	0.891	0.577

As presented in the above table, composite reliability (CR) ranged from0.807 to 0.921, all of which meet the criteria over 0.7. Average variance extracted (AVE) ranged from 0.512 to 0.646, all of which meet the criteria over 0.5. The results of CR and AVE all reached the convergence validity standard.

Discriminant validity

Discriminant validity requires differences between latent variables. To be specific, the square root of AVE of a latent variable is greater than its correlation coefficient with other latent variables, which can indicate that this latent variable is more closely related to its own factor than other latent variable factors, thus achieving discriminant validity. As can be seen from Table 4.23, all latent variables meet the requirement of discriminant validity standard.

Table 4.23 Discriminant validity for measurement model

	AVE	UB	BI	CQ	PI	FC	SE	SI	EE	PE
UB	0.577	**0.760**								

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Table 4.23 (continue)

	AVE	UB	BI	CQ	PI	FC	SE	SI	EE	PE
BI	0.617	0.539	**0.785**							
CQ	0.596	0.288	0.519	**0.772**						
PI	0.512	0.344	0.450	0.223	**0.716**					
FC	0.565	0.309	0.395	0.228	0.198	**0.752**				
SE	0.639	0.402	0.651	0.170	0.240	0.303	**0.799**			
SI	0.555	0.360	0.646	0.203	0.288	0.317	0.466	**0.745**		
EE	0.646	0.378	0.669	0.288	0.249	0.347	0.481	0.379	**0.804**	
PE	0.565	0.172	0.385	0.232	0.243	0.051	0.209	0.194	0.227	**0.752**

4.5 Findings of the Structural Equation Modelling

After reliability and validity testing, the model is improved and fully satisfied with the testing standards. Thus, structural equation model analysis can be implemented. The goodness-of-fit indexes are $\chi^2/df = 1.345$ (<5), CFI=0.977 (>0.9), GFI=0.907 (>0.9), TLI=0.975 (>0.9), RMSEA = 0.024 (<0.08), SRMR=0.066(<0.08), indicating that hypothesized model had satisfactory goodness of fit. The fit indices are listed in the Table 4.24. The results of structural equation model were obtained as shown in Figure 4.11.

Table 4.24 Fit indices for SEM

Indices	Criteria	Statistic value
X^2/df	< 5	1.345
GFI	> 0.9	0.907
CFI	> 0.9	0.977
NFI	> 0.9	0.915

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Table 4.24 (continue)

Indices	Criteria	Statistic value
TLI	> 0.9	0.975
RMSEA	< 0.05	0.024
SRMR	< 0.08	0.066

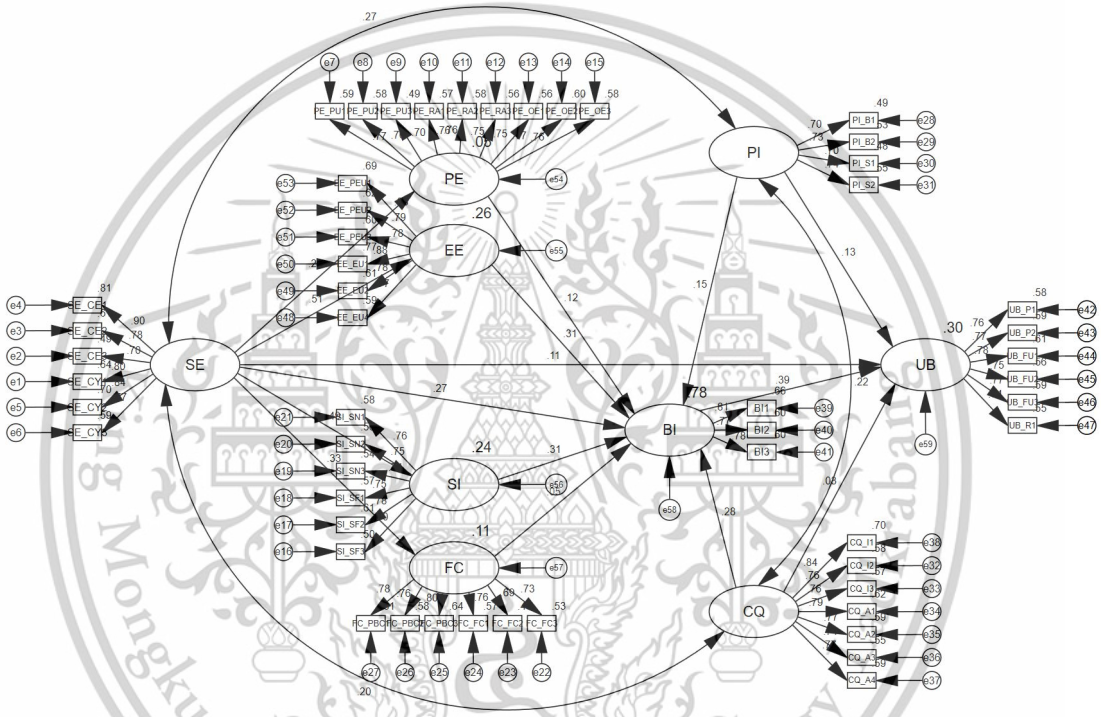

Figure 4.11 Structural Equation Model results

Results of effects of behavioral intention to use mobile learning

The empirical analysis to determine the effects of behavioral intention to use mobile learning was guided by the conceptual framework and the hypotheses, as presented in chapter 3.

Among the predictors of mobile learning behavioral intention, 6 out of 7 could predict behavior intention. In other words, H1, H2, H3, H5, H11, and H13 are consistent with the hypotheses. PE ($\beta = 0.125$), EE ($\beta = 0.31$), SI ($\beta = 0.31$), SE ($\beta = 0.268$), PI ($\beta = 0.151$), CQ ($\beta = 0.286$) all significantly affected the behavior intention of mobile learning. Specifically, the three additional factors, SE, PI, and CQ, were all found to be significant in

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predicting mobile learning behavior intention. Nevertheless, the results indicated that FC had no significant effect on behavioral intention. Therefore, H4 was not supported. The results of the analysis is presented below.

Table 4.25 Results of hypothesis for effects of behavioral intention

Paths	Decision Beta	p value	Result
H1: PE→BI	0.125	***	Supported
H2: EE→BI	0.31	***	Supported
H3: SI→BI	0.31	***	Supported
H4: FC→BI	0.052	0.101	NOT Supported
H5: SE→BI	0.268	***	Supported
H11: PI→BI	0.151	***	Supported
H13: CQ→BI	0.286	***	Supported

Note: ***significant at 0.001. PE = Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, FC = Facilitating Conditions, SE = Self-Efficacy, PI = Personal Innovativeness, CQ = Content Quality, BI = Behavioral Intention.

H1: Performance Expectancy will positively influence behavioral intention to use mobile learning.

Performance expectancy has a significant and positive effect on behavioral intention ($\beta = 0.125$, $p < 0.001$). The positive correlation indicated that a one-unit increase in PE caused a 0.125-unit increase in behavior intention to use mobile learning.

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H2: Effort Expectancy will positively influence Behavioral Intention to use mobile learning.

Effort expectancy has a significant and positive effect on behavioral intention ($\beta = 0.31$, $p < 0.001$). The positive correlation indicated that a one-unit increase in EE caused a 0.31-unit increase in behavior intention to use mobile learning.

H3: Social Influence will positively influence Behavioral Intention to use mobile learning.

Social influence has a significant and positive effect on behavioral intention ($\beta = 0.31$, $p < 0.001$). The positive correlation indicated that a one-unit increase in SI caused a 0.31-unit increase in behavior intention to use mobile learning.

H4: Facilitating Conditions will positively influence Behavioral Intention to use mobile learning.

Facilitating Conditions has an insignificant and positive effect on behavioral intention ($\beta = 0.052$, $p = 0.101$). It is observed that facilitating conditions did not have a significant effect on behavior intention to use mobile learning.

H5: Self-Efficacy will positively influence Behavioral Intention to use mobile learning.

Self-efficacy has a significant and positive effect on behavioral intention ($\beta = 0.268$, $p < 0.001$). The positive correlation indicated that a one-unit increase in SE caused a 0.268-unit increase in behavior intention to use mobile learning.

H11: Personal Innovativeness will positively influence Behavioral Intention to use mobile learning.

Personal innovativeness has a significant and positive effect on behavioral intention ($\beta = 0.151$, $p < 0.001$). The positive correlation indicated that a one-unit increase in PI caused a 0.151-unit increase in behavior intention to use mobile learning.

H13: Content Quality will positively influence Behavioral Intention to use mobile learning.

Content quality has a significant and positive effect on behavioral intention ($\beta = 0.286$, $p < 0.001$). The positive correlation indicated that a one-unit increase in CQ caused a 0.286-unit increase in behavior intention to use mobile learning.

Results of effects of use behavior of mobile learning

The empirical analysis to determine the effects of use behavior of mobile learning was guided by the conceptual framework and the hypotheses, as presented in chapter 3.

Among the predictors of mobile learning usage behavior, only BI and PI exhibited

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significant effects, with β=0.387 and β=0.129, respectively. These findings supported H12 and H15. Among the three additional variables, only PI had a significant effect on usage behavior. The results indicated that SE and CQ had no significant effect on use behavior. Consequently, H6 and H14 were not supported. The results of the analysis is presented below.

Table 4.26 Results of hypothesis for effects of use behavior

Path	Decision Beta	p-value	Result
H6: SE→UB	0.106	0.075	NOT Supported
H12: PI→UB	0.129	0.007	Supported
H14: CQ→UB	0.029	0.549	NOT Supported
H15: BI→UB	0.387	***	Supported

Note: *** is significant at 0.001. SE = Self-Efficacy, PI = Personal Innovativeness, CQ = Content Quality, BI = Behavioral Intention. UB = use behavior

H6: Self-Efficacy will positively influence Use Behavior of mobile learning.

Self-efficacy has a significant and positive effect on use behavior ($\beta = 0.106$, $p = 0.075$). It is observed that self-efficacy did not have a significant effect on use behavior of mobile learning.

H12: Personal Innovativeness will positively influence Use Behavior of mobile learning;

Personal innovativenes has a significant and positive effect on use behavior ($\beta = 0.129$, $p < 0.001$). The positive correlation indicated that a one-unit increase in PI caused a 0.129-unit increase in use behavior of mobile learning.

H14: Content Quality will positively influence Use Behavior of mobile learning;

Content quality has a significant and positive effect on use behavior ($\beta = 0.029$, $p = 0.549$). It is observed that content quality did not have a significant effect on use behavior of mobile learning.

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H15: Behavioral Intention will positively influence Use Behavior of mobile learning.

Behavioral intention has a significant and positive effect on use behavior ($\beta = 0.387$, $p < 0.001$). The positive correlation indicated that a one-unit increase in BI caused a 0.387-unit increase in use behavior of mobile learning.

Mediation effect

Based on previous results, it can be reasonably assumed that SE has a direct impact on BI. Here will discuss the indirect impact of SE on BI through PE, EE, SI, and FC. The results demonstrated that SE exerted a significant influence on PE, EE, SI, and FC, with path coefficients of 0.224, 0.5, 0.484, and 0.325, respectively. Consequently, hypotheses H7, H8, H9, and H10 were validated. The effects of self-efficacy on PE, EE, SI and FC are presented in Table 4.27.

Table 4.27 Results of hypothesis for effects of self-efficacy

Path	Decision Beta	p value	Result
H7: SE→PE	0.224	***	Supported
H8: SE→EE	0.5	***	Supported
H9: SE→SI	0.484	***	Supported
H10: SE→FC	0.325	***	Supported

Note: *** is significant at 0.001. PE = Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, FC = Facilitating Conditions, SE = Self-Efficacy.

H7: Self-Efficacy will positively influence Performance Expectancy.

Self-efficacy has a significant and positive effect on performance expectancy ($\beta = 0.224$, $p < 0.001$). The positive correlation indicated that a one-unit increase in SE caused a 0.224-unit increase in performance expectancy.

H8: Self-Efficacy will positively influence Effort Expectancy.

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Self-efficacy has a significant and positive effect on effort expectancy ($\beta = 0.5$, $p < 0.001$). The positive correlation indicated that a one-unit increase in SE caused a 0.5-unit increase in effort expectancy.

H9: Self-Efficacy will positively influence Social Influence.

Self-efficacy has a significant and positive effect on social influence ($\beta = 0.484$, $p < 0.001$). The positive correlation indicated that a one-unit increase in SE caused a 0.484-unit increase in social influence.

H10: Self-Efficacy will positively influence facilitating conditions.

Self-efficacy has a significant and positive effect on facilitating conditions ($\beta = 0.325$, $p < 0.001$). The positive correlation indicated that a one-unit increase in SE caused a 0.484-unit increase in facilitating conditions.

Given that FC exerts no significant influence on BI, three of the four mediation effects are significant. However, the SE→FC→BI pathway is rejected. In other words, SE exerted a significant indirect influence on the intention to use mobile learning, which was mediated by PE, EE, and SI. The indirect effect of the three path can be calculated from the direct effects. The indirect effect of SE→PE→BI is equal to the product of the two direct effects, that is $0.125 \times 0.224 = 0.028$. The indirect effect of SE→EE→BI is equal to the product of the two direct effects, that is $0.31 \times 0.5 = 0.155$. The indirect effect of SE→SI→BI is equal to the product of the two direct effects, that is $0.31 \times 0.484 = 0.150$. The total effect contains direct and indirect effects, so add up the two effects. The direct and indirect effects are presented in Table 4.28

Table 4.28 Mediation tests

Paths	Direct effect	Indirect effect	Total effect	Result
SE→PE→BI	0.268	0.028	0.296	Supported
SE→EE→BI	0.268	0.155	0.432	Supported
SE→SI→BI	0.268	0.150	0.418	Supported
SE→FC→BI	0.268		0.268	Not supported

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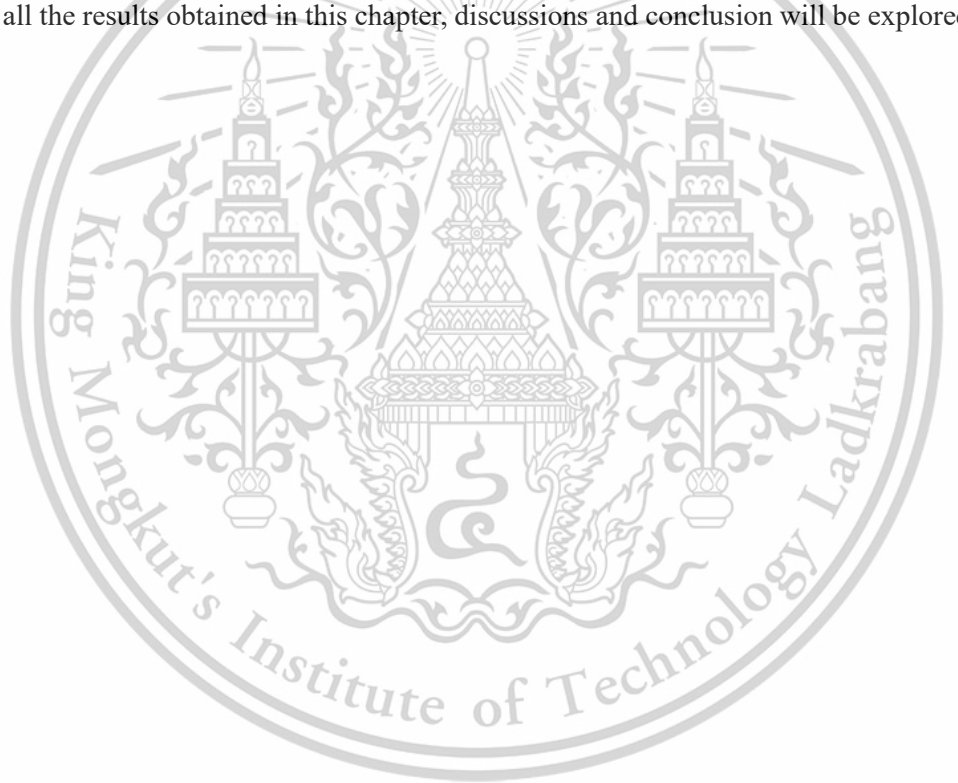
4.6 Conclusion

This chapter first gave a descriptive statistic of the demographic variables used in the data, explaining the sample characteristics. Then the descriptive statistics of the respondents regarding the nine latent variables. The frequency and percentage of each question were reported. The mean and standard deviation of each question, observed variable and latent variable were presented. Then the normality test was carried out and confirmed that the collected data is feasible for the follow-up step. Next the results of the measurement model including validity and reality test were reported. Last the findings of the Structural Equation Modelling (SEM) were reported and confirm 12 out of 15 hypotheses were supported. Based on all the results obtained in this chapter, discussions and conclusion will be explored.



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CHAPTER 5

DISCUSSIONS AND CONCLUSIONS

Based on the extended UTAUT model, this study examines the primary factors influencing behavioral intention and the actual use of mobile learning among Chinese higher vocational students. This study incorporated three additional variables—self-efficacy, personal innovativeness, and content quality—to explore the factors affecting mobile learning usage from both personal and quality perspectives.

5.1 Discussions

The discussions of this research is organized according to the research questions, to evaluate whether the findings agree or disagree with previous researches.

5.1.1 Self-efficacy, personal innovativeness, and content quality Effect of self-efficacy

SE was referenced in the study proposed UTAUT model, yet SE was not selected as a predictor in this paper (Venkatesh et al., 2003). Nevertheless, in recent years, an increasing number of studies have focused on the direct and indirect effects of SE on behavioral intention. The present study sought to ascertain the influence of self-efficacy on behavioral intention and actual use of mobile learning. The results indicated that SE only influenced behavioral intention, which was consistent with the findings of Kumar et al. (2020), Han & Shin (2016), Mohammadi (2015), and Almaiah et al. (2019) in the context of mobile learning. Additionally, the results supported the conclusions of Tarhini et al. (2021), Yeop et al. (2019), and Mahdi (2014) in the context of information technology. The findings indicate that when students possess adequate computer skills, they are more inclined to utilize technology. Consequently, it can be inferred that colleges should consistently cultivate students' abilities by conducting training courses on the effective utilization of mobile learning systems.

This study also found that self-efficacy positively predicted students' PE and EE, which is consistent with previous research by Li et al. (2020) and Shaya et al. (2023). This finding

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also aligns with Islam (2016), Bin et al. (2020), Chena et al. (2019), and Zheng & Li (2020), where researchers used terms such as perceived ease of use and usefulness. One explanation for this phenomenon can be found in Bandura's (1997) work, which posits that self-efficacy is a crucial factor in individuals' acceptance, implementation, and adherence to specific behaviors. When an individual possesses a robust sense of self-efficacy regarding mobile learning, it may be easier for him to perceive the technology as useful and straightforward to utilize (Chen et al., 2019). Chao (2019) discovered that students with high self-efficacy tend to derive enjoyment from using mobile learning. In addition, they not only find mobile learning easy to use but also acknowledge the importance of learning. This study found that SE influences on SI and FC, which corresponds with the findings of Li et al. (2020), Yeap et al. (2016), and Kumar et al. (2020). These findings suggest that students with a strong sense of self-efficacy are more likely to adopt suggestions from important people and are better at discovering mobile learning resources. Consequently, we demonstrated that self-efficacy exerts an indirect influence on behavioral intention via PE, EE, and SI. Consequently, higher vocational colleges should prioritize the factors that enhance students' self-efficacy.

Effect of personal innovativeness

Regarding the second personal factor, the findings indicated that personal innovativeness had a positive effect on intention to use mobile learning, in line with the results of previous studies by Lisana et al. (2023), Kim et al. (2017), and Alturki & Aldraiweesh (2022). Furthermore, personal innovativeness was found to be a significant predictor of actual use of mobile learning, aligning with the findings of Farooq et al. (2017), Pinho et al. (2021), and Larsen & Sorebo (2005) in the context of information systems (IS) adoption. This study corroborates the significance of PI on UB in the context of mobile learning. Those with a high level of innovativeness enjoy the use of high-tech system and services because they are more willing to take risks than others (Thakur et al., 2016). When students consider deciding whether to use innovative technologies, they do so not only based on scientific facts, but subjectively. Therefore, more consideration should be given to students' psychological characteristics, such as their attitudes towards learning and learning media, to understand their views on the adoption of mobile learning. This enables mobile learning developers to design

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innovative functions attracting students based on their learning preferences in order to encourage students to reach a higher level of personal innovativeness.

Effect of content quality

The content quality was found to influence the intention to use mobile learning. This implies that providing students with accurate, relevant, timely, and engaging content is crucial. Previous studies have also examined the impact of content quality on intention (Lutfi et al., 2022; Almaiah & Alismaiel, 2019; Mohammadi, 2015). Some of these studies use the term as "information quality". Additionally, the results suggest that designers of mobile learning application content should consider students' needs. Beyond basic information requirements, such as accuracy and timeliness, designers should focus on content formats like graphics, charts, videos, and animations to make learning more vivid and attractive through mobile learning applications. A crucial aspect of mobile learning is the provision of supplementary learning content to cater to the diverse needs of learners, ensuring that they derive enjoyment from the learning process. Conversely, if the available learning resources are inadequate and the practicality is poor, the experience will be perceived as meaningless by the learners, leading to a lack of acceptance or even rejection of mobile learning. Consequently, colleges and mobile learning developers should integrate existing learning resources and create targeted content based on students' preferences and characteristics. This approach is essential for the sustainable development of mobile learning. In this research, content quality was shown not to affect the use behavior of mobile learning. One possible explanation of this may be that some of the students in colleges are forced to use mobile learning platform as mobile learning usage is part of their final grade. It is a behavior that they don't need to decide no matter how attractive the content is.

5.1.2 The extended UTAUT model

5.1.2.1 Factors influencing BI

The results of this study show that PE, EE, SI, SE, PI and CQ are factors affecting BI, among which EE and SI are the most significant predictors ($\beta = 0.31$), which is consistent with the conclusions of Al-Adwan, Al-Adwan & Berger (2018) and Sidik & Syafar (2020). This suggested that the more students perceive mobile learning as an easy tool to use for

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learning activities, the more they would engage in mobile learning (Al-Adwan, Al-Adwan & Berger, 2018). Also, students' intention to use mobile learning was affected by the classmates, teachers and college supports. This result indicates that students do not develop their decisions in isolation from their social environment. The factors affecting BI followed are CQ ($\beta = 0.286$) and SE ($\beta = 0.268$), which are two additional variables. This suggests that colleges should improve the students' self-confidence for mobile learning and pay more attention to the content of learning resources on the mobile learning platforms.

For the UTAUT model, many researchers have identified four constructs that significantly impact mobile learning behavioral intention (Venkatesh et al., 2012; Sik & Syafar, 2020; Al Adwan, Al-Madadha, & Zvirzdinaite, 2018). However, in this study, facilitating conditions did not significantly affect mobile learning behavioral intention, consistent with Alowayr (2019). This indicates that students are not concerned with the infrastructure and technical support of mobile learning technology.

Effect of PE on BI

Based on the findings, performance expectancy has a significant and positive effect on behavioral intention ($\beta = 0.125$, $p < 0.001$). PE is a predictor of intention to use, meaning that students tend to use a technology when they think it will help them improve their learning outcomes (Alowayr, 2019). The result is in line with previous study. The study conducted by Tarhini et al. (2021) found out that performance expectancy has a significant influence on intention to use e-learning. Additionally, a study by Alshehri et al. (2019) indicated that performance expectancy significantly influenced the intention to use a learning management system. Among three observed variables of PE, relative advantage had the highest mean of 3.76. In relative advantage, the item "using the M-learning increases my productivity" is most important which indicates the more students believe mobile learning can increase their productivity, the more they will intend to use it.

Effect of EE on BI

Based on the findings, effort expectancy has a significant and positive effect on behavioral intention ($\beta = 0.31$, $p < 0.001$). EE is a most important predictor of intention to use in this study. The result is consistent with previous study. The study conducted by Al-Adwan et al. (2018) found out that effort expectancy has a significant influence on intention to use

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mobile learning. Additionally, a study by Sidik & Syafar (2020) indicated that effort expectancy significantly influenced the intention to use mobile learning. Among two observed variables of EE, perceived ease of use had the higher mean. In perceived ease of use, the item "I would find M-learning easy to use" is most important with a mean of 3.65 which indicates the more students believe mobile learning is easy to use, the more they will use it.

Effect of SI on BI

Based on the findings, social influence has a significant and positive effect on behavioral intention ($\beta = 0.31$, $p < 0.001$). SI is a most important predictor of intention to use in this study. The result is consistent with previous study. The study conducted by Al-Adwan et al. (2018) found out that SI has a significant influence on intention to use mobile learning. Additionally, a study by Sidik & Syafar (2020) indicated that SI significantly influenced the intention to use mobile learning. Among all the item of SI, the item "The lecturers and other staff at my college are helpful in the use of M-learning" is most important with a mean of 3.82 which indicates the help from lecturers and staff for students can contribute to the intention to use mobile learning.

Effect of FC on BI

Based on the findings, facilitating conditions has an insignificant and positive effect on behavioral intention ($\beta = 0.052$, $p = 0.101$). FC has no significant effect on mobile learning behavioral intention in this study, which is consistent with Alowayr (2019). This means that students did not concern in terms of infrastructure and technical support of the mobile learning technology. Meet et al. (2022) concluded differently, that FC had a significant impact on intention to use MOOC in generation Z.

Effect of SE on BI

Based on the findings, self-efficacy has a significant and positive effect on behavioral intention ($\beta = 0.268$, $p < 0.001$). SE is a predictor of intention to use in this study. The finding is line with the conclusion of Kumar et al. (2020), whose study found out that SE has a significant influence on intention to use mobile learning. Additionally, a study by Yeop et al. (2019) indicated that SE significantly influenced the intention to use blended learning approach. Among two observed variables of SE, capability had the higher mean. In capability, the item "I have the ability to use all mobile-learning technology features" is most important

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with a mean of 3.72 which indicates the more capable of mobile learning technology the students are, the more likely they will use it.

Effect of PI on BI

Based on the findings, personal innovativeness has a significant and positive effect on behavioral intention (β= 0.151, $p < 0.001$). PI is a predictor of behavioral intention to use in this study. The finding is line with the conclusion of Lisana et al. (2023), whose study found out that PI has a significant influence on intention to use mobile learning. Additionally, a study by Kim et al. (2017) indicated that PI significantly influenced the intention to use mobile learning. Among two observed variables of PI, behaviors had the higher mean. In behaviors, the item "If I heard about a new M-learning technology, I look for ways to experiment with it" is most important with a mean of 3.61 which indicates the more students experiment with mobile learning, the more they intend to use it.

Effect of CQ on BI

Based on the findings, content quality has a significant and positive effect on behavioral intention (β= 0.286, $p < 0.001$). CQ is a predictor of behavioral intention to use in this study. The finding is line with the conclusion of Lutfi et al. (2022), whose study found out that CQ has a significant influence on intention to use mobile learning. Additionally, a study by Almaiah & Alismaiel (2019) indicated that CQ significantly influenced the intention to use mobile learning system. Among two observed variables of CQ, informativeness had the higher mean. In informativeness, the item "mobile learning application provides accurate content" is most important with a mean of 3.84 which indicates the more students believe mobile learning provide accurate content, the more they intend to use it.

5.1.2.2 Factors influencing UB

The study posited that PI and BI exert a direct influence on UB. As anticipated, BI was found to have a significant direct effect on UB, in alignment with numerous prior studies (Almaiah, Alamri, & Al-Rahmi, 2019; Almaiah & Alismaiel, 2019; Lutfi et al., 2022; Farooq et al., 2017). Among the three additional variables, only personal innovativeness has been verified as the factor that has a direct impact on actual use, which is consistent with the results of these studies (Almaiah, Alamri & al-Rahmi, 2019; Seliana et al., 2020; Elmunsyah et al.,

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2023; Celik & Ayaz, 2022). The findings of this research provide guidance for higher vocational colleges and decision-makers in China regarding the implementation of mobile learning.

Effect of SE on UB

Based on the findings, self-efficacy has an insignificant and positive effect on use behavior (β= 0.106, p = 0.075). SE did not have a significant effect on use behavior in this study. Evaluating previous study, Rahmawati (2019) had results that SE has a significant impact on use behavior of E-learning. Also, Lwoga & Komba (2015) had results that SE has a significant impact on use behavior of web-based learning.

Effect of PI on UB

Based on the findings, personal innovativeness has a significant and positive effect on use behavior (β= 0.129, p = 0.007). PI is a predictor of use behavior of mobile learning in this study. The finding is line with the conclusion of Farooq et al. (2017), whose study found out that PI has a significant influence on use behavior of Lecture Capture System. Additionally, a study by Pinho et al. (2021) indicated that PI significantly influenced use behavior of E-learning.

Effect of CQ on UB

Based on the findings, content quality has an insignificant and positive effect on use behavior (β= 0.029, p = 0.549). CQ did not have a significant effect on use behavior in this study. Evaluating previous study, Elmunsyah et al. (2023) found out that CQ has a significant influence on use behavior of learning management system. Additionally, a study by Seliana et al. (2020) indicated that CQ significantly influenced use behavior of E-learning.

Effect of BI on UB

Based on the findings, behavioral intention has a significant and positive effect on use behavior (β= 0.387, p < 0.001). BI is a predictor of use behavior of mobile learning in this study. The finding is line with the conclusion of Farooq et al. (2017), whose study found out that BI has a significant influence on use behavior of Lecture Capture System. Additionally, a study by Bin et al. (2020 indicated that BI significantly influenced use behavior of new technology.

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5.1.3 Model verification effect

In this study, the extended Unified Theory of Acceptance and Use of Technology (UTAUT) model was employed to investigate the factors influencing the intention to engage in mobile learning and the actual use of mobile learning. The results demonstrate that the influence relationships posited by the original UTAUT model are indeed valid. That is to say, the constructs of PE, EE, and SI exert a positive effect on behavioral intention, and behavioral intention, in turn, affects use behavior. The original UTAUT model did not hypothesize the effect of FC on behavioral intention. Among the factors that affect the behavior intention of mobile learning, the most significant are EE and SI, followed by CQ and SE, and least are PI and PE. This study demonstrated the theoretical validity of the UTAUT model. The UTAUT model has been empirically tested by numerous researchers, and the results may vary depending on the specific educational and cultural contexts.

This study found that PE was the least significant among several factors (β=0.125), while in UTAUT or its extended models, the results of other studies showed that PE was the most significant (Abbad, 2021; Alowayr, 2021; Almaiah et al., 2019). The results of this study diverge from those of previous studies, and one potential explanation is that the subject of this study is students in higher vocational colleges, whereas previous studies have focused on university students. Higher vocational college students exhibit a weaker motivation to learn and a more pessimistic outlook regarding the potential impact of their educational experiences.

5.2 Conclusions

This study employed the extended UTUAT model to investigate the factors influencing behavioral intention and use behavior of mobile learning in Chinese higher vocational colleges. In addition to the original model, three additional variables were incorporated: self-efficacy, personal innovativeness, and content quality. The study concluded that the model applied in this study satisfied all the requirements, including the reliability, validity, and model fitness thresholds, which implies that the results presented can be trusted.

The results indicate that the three additional variables--self-efficacy, personal

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innovativeness and content quality are significant in predicting the intention and actual use of mobile learning. Self-efficacy exerts a direct and indirect influence on behavioral intention to use mobile learning. Self-efficacy can indirectly affect behavioral intention through the mediation of PE, EE and SI. Personal innovativeness is a determining factor in both the behavioral intention to use mobile learning (BI) and the use behavior of mobile learning (UB). Content quality is a determining factor in the intention to use mobile learning.

The most important factors have been identified. The most influential predictors of BI are EE and SI, followed by CQ and SE. The least influential predictors are PI and PE. The most influential predictor of UB is BI, followed by PI.

The extended UTAUT model has been validated as a useful tool to explain the adoption of mobile learning. This study contributes to the existing literature on the UTAUT model by confirming its applicability to BI and UB in the context of Chinese higher vocational colleges. The findings demonstrate that PE, EE, and SI collectively influence BI in relation to mobile learning. Nevertheless, FC is not statistically significant.

5.3 Implications

The results obtained from this study make important contributions towards extending the theoretical and practical knowledge as far as the use of moible learning by the students is concerned. It also provides other suggestions for developing and improving the application of the concepts through managerial implications. These implications are discussed in this section.

5.3.1 Theoretical Implications

Theoretically, this research applied a model which investigated the factors affecting students' behavioral intention to use mobile learning. The model was developed in reference to the Unified Theory of Acceptance and Use of Technology (UTAUT) model, as Venkateshet al. (2003) developed. This research Indicated the validity of using UTAUT on mobile learning.

Furthermore, previous literature has over-relied on PE and EE as the primary salient

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beliefs when predicting student adoption of mobile learning, undermining understanding of mobile learning acceptance and potential adoption strategies. According to the UTAUT model, four major constructs determine the behavioral intention and the use behavior. These constructs include performance expectancy, effort expectancy, social influence and facilitating conditions. The model of this research extended this theoretical foundation by incorporating three additional variables, self-efficacy, personal innovativeness and content quality. Self-efficacy is a concept discovered by Bandura in explaining social cognitive theory (Bandura, 1977) and is defined as a personal judgment of how well one can execute courses of action required to deal with prospective situations fraught with several unpredictable and stressful elements (Bandura, 1982). Personal Innovativeness represents an individual's willingness to take a risk and try a new technology (Agarwal & Prasad, 1998). Content quality is a critical factor for the success of the information systems (DeLone & McLean, 1992). The inclusion of these constructs in the theoretical model proposed by Venkatesh et al. (2003) has proved vital as there are no results indicating that they significantly influence the behavioral intention and use behavior of mobile learning. To be specific, based on the results of this research, self-efficacy, personal innovativeness and content quality played an important role in predicting behavioral intention of mobile learning. Such a contribution broadens the reach of this research in terms of understanding the basis and motivations of students' intention to use mobile learning.

5.3.2 Practical Implications

The findings of this study benefit both students and educational institutions. The research can help colleges and teachers better understand the factors affecting students' use of mobile learning to promote the transformation of learners' learning methods, help teachers to develop and select high quality mobile learning courses, improve teaching quality and promote the application of vocational education informatization. When selecting mobile learning programs and platforms, colleges and teachers should prioritize the predictors identified in this study. They should choose platforms that offer the greatest ease of use, highest content quality, and desired performance. It is recommended that colleges facilitate student awareness of the advantages of mobile learning and foster a sense of confidence in their ability to utilize

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mobile learning. When students feel confident and satisfied with the mobile learning platforms, they will utilize them more frequently and achieve superior learning outcomes.

The results of this study indicate the necessity for numerous implications. Primarily, educators should provide students with a plethora of diverse resources and personalized guidance through mobile learning platforms, allowing students to pursue individualized learning based on their specific needs. Additionally, educators should leverage the capabilities of big data to oversee students' learning behaviors and promptly adjust teaching strategies through system feedback. Secondly, higher vocational education institutions should proactively develop talent training models that align with the specific job requirements and work environments of students across different majors. They should also continuously integrate and leverage mobile learning platforms to provide students with a diverse range of teaching resources. Third, teachers should be encouraged to share their experiences with mobile learning and participate in teaching observation, exchange, and other activities. This will facilitate the creation of a repository of knowledge that can inform the practices of other teachers in higher vocational colleges. By doing so, the potential of mobile learning can be more effectively harnessed, and its impact can be enhanced in these institutions. Fourth, teachers in higher vocational schools can set up teams to design and produce mobile learning courses according to their students' characteristics, so as to achieve better results. According to the results of the study, although content quality does not affect the use of mobile learning, it still affects the decision of teachers or colleges. Teachers will adjust the use of the next stage according to the actual performance of the use of the platform. High-quality mobile learning content will be reasonably arranged and explained according to the cognitive characteristics and learning basis of vocational college students, which will help students better understand and master professional knowledge and skills, and improve their learning performances.

5.4 Limitations and Recommendations

5.4.1 limitations

This research has some limitations. First, it focuses only on Chinese higher vocational

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colleges. Therefore, the application of the findings of this study should consider this context. If the scope of sample collection can be expanded, the entire study can be made more comprehensive and convincing. Second, this research did not include any control constructs. The control variables may change the strength of the independent variable's influence on the dependent variable, which can help to identify causal relationship more accurately. Third, this study adopted only the quantitative technique and the data were analyzed statistically. Therefore, the findings of this study are entirely based on the statistical analysis of the data collected. However, some important insights could also be developed through qualitative analysis. Last, this research found that self-efficacy and content quality positively affected behavior intention but did not affect use behavior. This research has given some possible explanations. The reason for the phenomenon can be explored in more depth.

5.4.2 Recommendations

First, expand the scope of the sample as much as possible in order to make the entire study more comprehensive and convincing. Future studies could also examine K-12 schools or universities. Second, control variables can be incorporated into the model in the future research. Third, future studies should consider using both qualitative and quantitative techniques to gain a deeper understanding of specific factors. Last, the additional factors in this research can be investigated further and gain more results and to explain more phenomenon in colleges or universities, and provide more useful strategies for educators and developers.

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APPENDIX

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APPENDIX A

Questionnaire

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APPENDIX A

QUESTIONNAIRE

The questionnaire designed for this study will be divided into 4 parts:

Part 1: Questions on the demographic information

Part 2: Questions on the internet knowledge and experience

Part 3: Questions on the latent and observed variables of the UTAUT model from mobile learning perspective.

Part 4: Questions about Self-efficacy, Personal Innovativeness and Content Quality from mobile learning perspective.

Part 5: Suggestions

Part 1: Questions on the demographic information

如果学生在正在读大一的第一学期，他就不用回答问卷。

If the student is in the first semester of his freshman year, he/she does not have to answer the questionnaire.

第一部分：受访者个人信息

1. Gender （性别）：

☐ male 男　　☐ Female 女

2. Age 年龄：

☐ 18-19　　☐ 20-21　　☐ 22-23　　☐ 24 以上 （over 24）

3. Grade 年级：

☐ Freshman year 大一

☐ Sophomore year 大二

☐ Junior year 大三

4. Region 所在地区：

☐ Northeast 东北 (Heilongjiang, Jilin, Liaoning 黑龙江，吉林，辽宁)

☐ North 华北 (Beijing, Tianjin, Hebei, Shanxi (Taiyuan), Neimenggu 北京，天津，河北，山西，内蒙古)

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☐ Northwest 西北 (Shanxi, Gansu, Qinghai, Ningxia, Xinjiang 陕西，甘肃，青海，宁夏，新疆)

☐ Central 华中 (Henan, Hunan, Hubei 河南，湖南，湖北)

☐ East 华东 (Shandong, Jiangsu, Anhui, Shanghai, Zhejiang, Jiangxi, Fujian 山东，江苏，安徽，上海，浙江，江西，福建)

☐ Southwest 西南 (Chongqing, Guizhou, Sichuan, Yunnan, Xizang 重庆，贵州，四川，云南，西藏)

☐ South 华南 (Guangdong, Hainan, Guangxi 广东，海南，广西)

Part 2: Questions about the internet knowledge and experience

5. How long do you use mobile phone for internet per day?

(你每天花多少时间手机上网？)

☐ less than 1 hour (1 小时以内) ☐1-2 hours(1-2 小时)

☐ more than 2 hours (2 小时以上)

6. How long have you used M-learning?

☐ 0-1year (0-1 年) ☐ 1-2 years (1-2 年) ☐ 2 years and more (2 年以上)

Part 3: Questions on the latent and observed variables of the UTAUT model from mobile learning perspective.

Question		Least → Most				
		1	2	3	4	5
	Use behavior					
7	**Preference:** I prefer to use M-learning when available. 条件允许的情况下，我更倾向于使用移动学习。					
8	I aim to use M-learning instead of traditional ones. 我倾向使用移动学习而不是传统的。					
9	**Frequently use:** I use M-learning daily.					

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	我每天使用移动学习。
10	I use M-learning sometimes. 我偶尔使用移动学习。
11	I will use M-learning daily in the future. 在未来，我会每天使用移动学习。
	Recommendation:
12	I recommend M-learning for others to use. 我会把移动学习推荐给其他人。
Behavioral Intention	
	Intention:
13	I intend to use M-learning in the future (from subjective perspective). 我想要在未来使用移动学习（从主观的角度）。
	Prediction:
14	I predict I would use M-learning in the future (have a large chance). 我预测将来会使用移动学习（从可能性的角度）。
	Planning:
15	I plan to use M-learning in the future. 我计划在未来使用移动学习。
	Performance Expectancy
	Perceived Usefulness:
16	I would find M-learning useful in my learning. 在我的学习过程中，我认为移动学习很有用。
17	Using M-learning would make it easier for my learning. 我认为使用移动学习会让我的学习变得更容易。
18	Using M-learning would improve my learning performance.

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	我认为使用移动学习将提高我的学习成绩。
19	Using M-learning would help me prepare before class and review after class. 我认为使用移动学习可以帮助我课前预习，课后复习。
20	**Relative Advantage：** Using the M-learning enables me to accomplish tasks more quickly. 使用移动学习帮我更快的完成任务。
21	Using the M-learning increases my productivity. 使用移动学习提高了我的效率。
22	Using M-learning system increases the quality of learning process. 使用移动学习提高了学习质量。
23	**Outcome Expectation：** Using M-learning platforms will increase my chances of learning things that are important to me. 使用移动学习给我更多学习重要知识的机会。
24	If I use M-learning, my classmates will perceive me as competent. 如果我使用移动学习，我的同学会觉得我很有能力。
25	Using M-learning will increase my chances of getting a better grade. 使用移动学习增加我获得更好成绩的机会。
	Effort Expectancy
26	**Perceived Ease of Use：** My interaction with M-learning would be clear and understandable. 我认为我与移动学习的互动将会是清晰易懂的。

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27	It would be easy for me to become skillful at using the M-learning. 对我来说熟练使用移动学习是很容易的。
28	I would find M-learning easy to use. 我认为移动学习很容易使用。
29	**Ease of Use：** Learning to operate M-learning is easy for me. 学习操作移动学习对我来说很容易。
30	I find it easy to get M-learning to do what I want it to do. 我发现让移动学习做我想做的事情很容易。
31	I can easily understand the knowledge points explained by mobile learning. 我可以很容易地理解移动学习所讲解的知识点。
32	Overall, I believe that M-learning is easy to use. 总的来说，我相信移动学习很容易使用。
	Social Influence
33	**Subjective Norm：** People who influence my behaviour think that I should use M-learning. 影响我行为的人认为我应该使用移动学习。
34	People who are important to me think that I should use M-learning. 对我很重要的人认为我应该使用移动学习。
35	My classmates and teachers think that I should use M-learning. 我的同学和老师都认为我应该使用移动学习。
36	**Social Factors：** The lecturers and other staff at my college are helpful

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	in the use of M-learning. 我的老师和学校其他工作人员在使用移动学习方面很有帮助。
37	I use M-learning because of the proportion of classmates who use M-learning. 我使用移动学习是因为使用移动学习的同学比例大。
38	In general, my college has supported the use of mobile learning. 总的来说，我所在的学校支持使用移动学习。
	Facilitating Conditions
39	**Perceived Behavioral Control：** I have the resources necessary to use M-learning system. 我有使用移动学习系统所需的资源。
40	I have the knowledge necessary to use M-learning. 我有使用移动学习系统的必要知识。
41	M-learning is compatible with other systems I use.移动学习与我使用的其他系统兼容。
42	**Facilitating conditions：** There is a specific person or group available for assistance with any technical problem I may encounter. 对于我可能遇到的任何技术问题，都有一个特定的人或团队可以提供帮助。
43	Specialized instruction concerning M-learning was available to me. 我可以得到关于移动学习专门的指导。
44	Using M-learning fits my learning style.

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	使用移动学习适合我的学习风格。
45	I would use M-learning if the teacher included M-learning (such as watching video hours) in the assessment of the course. 如果老师将移动学习(比如观看视频时长)纳入课程考核，我会使用移动学习。

Part 4: Questions about Self-efficacy, Personal Innovativeness and Content Quality from mobile learning perspective.

Question	Least → Most				
	1	2	3	4	5
Self-Efficacy					
46	**Confidence：** I am confident of using the mobile learning even if there is no one around to show me how to do it. 即使没有人告诉我怎么做，我也有信心使用移动学习。				
47	I am confident of using the mobile learning even if I have never used such a system before. 即使我以前从未使用过这样的系统，我也有信心使用移动学习。				
48	I am confident of using the mobile learning even if I have only the online instructions for reference. 即使只有在线指南作为参考，我也有信心使用移动学习。				
49	**Capability：** I have the ability to use all mobile-learning technology features. 我有能力使用所有移动学习的功能。				

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50	I have the ability to post comments and respond to comments posted via mobile learning. 我有能力在移动学习平台发表评论和回应评论。
51	I have the ability to locate information on the course when using mobile learning. 我有能力使用移动学习在课程页面上查找信息。
	Personal Innovativeness
52	**Behaviors:** I like to experiment new M-learning technologies. 我喜欢尝试新的移动学习技术。
53	If I heard about a new M-learning technology, I look for ways to experiment with it. 如果我听说了一种新的移动学习技术，我就会寻找方法去实践它。
54	**States:** Among my peers, I am usually the first to try out new M-learning technology. 在同龄人中，我通常是第一个尝试新的移动学习技术的人。
55	I am interested in M-learning technologies that are new to me. 我对那些新的移动学习技术很感兴趣。
56	In general, I am hesitant to try out new M-learning technologies (-). 总的来说，我对尝试新的移动学习技术犹豫不决(-)。
	Content Quality
57	**Informativeness:** Mobile learning provides accurate content.

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	移动学习提供准确的内容。
58	Mobile learning provides up to date content. 移动学习提供最新的内容。
59	Mobile learning provides content that is relevant to my needs. 移动学习提供了与我的需求相关的内容。
60	**Accessibility:** The content of the course provided by Mobile learning is easy to understand. 移动学习提供的课程内容简单易懂。
61	Mobile learning application provides timely content. 移动学习应用提供及时的内容。
62	It is easy to find the information that I need when using M-learning. 使用移动学习很容易找到我需要的信息。
63	The course content of mobile learning is more vivid than that of traditional classroom. 移动学习的课程内容比传统课堂更加生动。
64	The course provided by mobile learning can fast forward and play back, which can help us master the whole picture of the knowledge. 移动学习提供的课程可以快进和回放，可以帮助我们掌握知识的全貌。

Part 5:

65. Suggestions

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