International Science and Technology Journal
المجلة الدولية للعلوم والتقنية

Volume 37 العدد
Part 1 المجلد

http://www.doi.org/10.62341/fsaa0927

Received	2025/08/28	تم استلام الورقة العلمية في
Accepted	2025/09/26	تم قبول الورقة العلمية في
Published	2025/09/27	تم نشر الورقة العلمية في

Assessing to use of asynchronous virtual learning technologies in teaching education at Elmergib University

"A study of faculty members' acceptance and use of technology"

Fatimah Salih. Aljawadi
Department of Computer Science, Faculty of Arts and Sciences, Elmergib University, Qasr Khiar, Libya
fatimazalh39@gmail.com, fsejuwadi@elmergib.edu.ly

Abstract

This study aims to identify the variables impacting asynchronous virtual learning technologies adoption in teaching by faculty members at Elmergib University and use by applying the unified theory of acceptance and use of technology 2 (UTAUT2) with Trust as an external variable. A Google forms were used to collect 154 responses to an online questionnaires that were distributed to respondents as part of the data collection process for this study. This study's data analysis method used structural equation modeling (SEM), which was run with SmartPLS. The validity and reliability of the research extended model were assessed. The findings aid in closing the gap between users and technology. The result of this study shows that behavioral intention when using asynchronous virtual learning technologies in teaching is influenced by five elements in the modified UTAUT2 model which namely Performance Expectancy (PE), Facilitating Conditions (FC), Hedonic Motivation (HM), Price Value (PV) and Habit (HB). Meanwhile, variables such as Effort Expectancy (EE),

Social Influence (SI) and Trust(TR) did not show any influence of the behavioral intention of the asynchronous virtual learning technologies in teaching . Additionally, the results indicated that actual use behavior to implement asynchronous virtual learning technologies at Elmergib University highly depend on Behavioral Intention (BI) to the faculty members rather Habit (HB) and Facilitating Conditions (FC).

Keywords: Asynchronous virtual learning**.** UTAUT2, Elmergib University, Faculty members**.**

International Science and Technology Journal
المجلة الدولية للعلوم والتقنية

Volume 37 العدد
Part 1 المجلد

المجلة الدولية للعلوم والتقنية
International Science and Technology Journal
ISTJ

http://www.doi.org/10.62341/fsaa0927

تقييم استخدام تقنيات التعلم الافتراضي غير المتزامن في التدريس بجامعة المرقب

"دراسة حول قبول أعضاء هيئة التدريس واستخدامهم للتكنولوجيا"

فاطمة صالح الجوادى

قسم علوم الحاسوب، كلية الآداب والعلوم، جامعة المرقب، قصر الخيار، ليبيا

fatimazalh39@gmail.com, fsejuwadi@elmergib.edu.ly

الملخص

تهدف هذه الدراسة إلى تحديد المتغيرات التي تؤثر على تبني تقنيات التعلم الافتراضي غير المتزامن في التدريس من قبل أعضاء هيئة التدريس بجامعة المرقب واستخدامها من خلال تطبيق النظرية الموحدة لقبول واستخدام التكنولوجيا 2 (UTAUT2) مع الثقة كمتغير خارجي. تم استخدام نماذج قوقل لجمع 154 إجابة على الاستبيانات عبر الإنترنت التي تم توزيعها على المستجيبين كجزء من عملية جمع البيانات لهذه الدراسة. استخدمت طريقة تحليل البيانات في هذه الدراسة نمذجة المعادلات الهيكلية (SEM)، والتي تم تشغيلها باستخدام SmartPLS. تم تقييم صحة وموثوقية نموذج البحث الموسع. تساعد النتائج في سد الفجوة بين المستخدمين والتكنولوجيا. تُظهر نتيجة هذه الدراسة أن النية السلوكية عند استخدام تقنيات التعلم الافتراضي غير المتزامن في التدريس تتأثر بخمسة عناصر في نموذج UTAUT2 المعدل وهي الأداء المتوقع (PE) والعوامل الميسرة (FC) والتحفيز الممتع (HM) والقيمة السعرية (PV) والاعتياد (HB). في الوقت نفسه، لم تُظهر متغيرات مثل الجهد المتوقع (EE) والتأثير الاجتماعي (SI) والثقة (TR) أي تأثير على النية السلوكية لتقنيات التعلم الافتراضي غير المتزامن في التدريس. إضافةً إلى ذلك، أشارت النتائج إلى أن سلوك الاستخدام الفعلي لتطبيق تقنيات التعلم الافتراضي غير المتزامن في جامعة المرقب يعتمد بشكل كبير على النية السلوكية (BI) لدى أعضاء هيئة التدريس، وليس على الاعتياد (HB) والعوامل الميسرة (FC).

الكلمات المفتاحية: التعلم الافتراضي غير المتزامن، UTAUT2، جامعة المرقب، أعضاء هيئة التدريس.

http://www.doi.org/10.62341/fsaa0927

1. INTRODUCTION

COVID-19 pandemic has increased the demand for online education all over the world (Daniel, 2020; Murphy., 2020), raising the concern about the development of the digital revolution at the teaching stage (García-Peñalvo. & Corell, 2020). Online education becomes a common mean of instruction due to its flexibility, convenience, and learning pedagogy (Dhawan, 2020). Moreover, online education has a distinctive strength in teaching and learning because of the various and increasing students in education (Yanjun et al., 2021). In online learning, learners are not required to be in a specific pace during a schedule timetable, as it is known “study anywhere at any time”. That is, online education learners can enhance their formal and informal education through numerous digital platforms offered by online learning (Panda, 2024).

On the other hand, following online education does not mean that physical education, which is considered the natural teaching method, must be abandoned. Instead, it can be used as a beneficial opportunity. Hence, it could be an alternative for universities to have a complete educational catalogue to provide both online and blended learning degrees. The involvement of online education at universities helps universities to play a vital role in a market share that is in high demand and is predicted to increase rapidly over the next few years. Utilizing online learning at universities is not compulsory; however, when it is used, it must provide a high quality of teaching. It must be as expected of the institutional universities they represented, in order to be distinctive in a market with many exclusive offers of widely different forms and condition(García-Peñalvo, 2021).

The main goal of online education is to give all learners virtual educational environments that help them to have access to educational advantages wherever they are. For this reason, in order to provide learners with high quality education, teachers have to use advanced technologies to help learners become more proficient and incorporate into their practice professionally.

Technology also helps teachers to employ useful resources to improve their teaching as well as assisting students to learn (Budiman, 2017; Zulfitria et al., 2020). In this regard, teachers at schools or universities are the key element in integrating technology in teaching and learning process effectively. Teo (2014) indicated that teachers have the ability to decide on the kind, frequency, and amount of technological resources they should adopt when

http://www.doi.org/10.62341/fsaa0927

designing their curriculum and delivering lessons.

Two fundamental settings are frequently compared in online learning: asynchronous and synchronous. These settings are different in place and time of teaching and learning. For example, asynchronous is more learner-centered, less teacher dependent, and independent of time and place (Bernand et al., 2004; Murphy et al., 2011; Clark & Mayer, 2016; Xie et al., 2018). Asynchronous learning is flexible for learners; it is considered as an essential feature of effective online learning programs. In asynchronous learning, there are different learning methods since learners can select their own adventure. In other words, regarding to the order; they intend thoroughly to explore and comprehend the content and immerse themselves intensely in a specific subject. Since learners can access to the program and content from any place in the world using the internet, asynchronous learning is usually recognized as "independent learning". Asynchronous learning utilizes many systems and devices that help teachers and learners interact according to their suitable timetables (Bueno, 2020; Kistan et al., 2020).

In 2020, social interaction is noticeably limited in order to reduce the infection rates of Covid-19. Hence, all universities around the world were closed and most of the courses were provided online. Murphy (2020) described the situation of having all students learn from home for a long period of time as emergency online learning. Consequently, Libyan Ministry of Higher Education and Scientific Research recognizes the significance of online education as an effective alternative to improve the quality of education at Libyan universities. Due to the COVID-19 pandemic, Libyan policymakers are working very hard to develop an efficient strategy to make online education an essential element in the educational process. To the best knowledge of the researcher, there is a dearth of research on online education in Libyan educational system and this specific issue still needs to be broadly investigated (Ramadan et al., 2020).

Many universities all over the world rescheduled the academic calendar to adopt online education instead of physical education in an attempt to reduce COVID-19 infection. As a result, by the end of 2020, most educational systems worldwide adopt the online learning and students can go to the universities only to have their final exams. This online learning was a new experience for many universities and was adopted because of an emergent situation only. However, some universities did not have any previous experience

http://www.doi.org/10.62341/fsaa0927

of online learning; while others did. Moreover, some universities try to train instructors and students on the use of online platforms successfully in order to follow the educational plan; while other universities decided to wait to return to physical education safely. Suwaed (2020) mentioned that the decision of using online learning was left to instructors and students.

Knowledge about online learning will inform the decision makers on the best way to improve the educational system in order to enrich users' experience; thereby ensuring its adoption and implementation. It is very crucial to clarify that the usage and acceptance of information systems (IS) are key elements in the success of IS. It might be difficult to encourage students to use online learning if their expectations are not met. This explains the reason behind why some students may or may not be willing to use technology in learning, which is a continuous concern for IS studies (Tamilmani et al., 2020). Many studies examined how instructors' and students' acceptance of digital formats changed in the context of Covid-19, how this would impact higher education in the future (Vallaster & Sageder, 2020), and perception of experienced instructors' towards online teaching (Rapanta et al., 2020).

1.1 Aims of study

Majority of teachers and students in all educational setting in the world were not well-prepared to transfer from physical education to online education. However, they had to accept and implement this unexpected method during the Covid-19pandemic (Khan et al., 2019). Therefore, when introducing any new teaching methods, including technological innovations, it is very essential to assure that teachers and students are ready to accept and employ these methods effectively. If the educational administrations have a better understating of the educators' perception about online learning, then, they can employ the strategic plans successfully (Vaca-Cárdenas et al., 2024).

This paper focused on the teaching mission using asynchronous online. Faculty members have a key role in successful implementing of asynchronous online. To bridge this research gap, the UTAUT2 is applied to identify the factors that influence the acceptance of asynchronous virtual learning technologies by faculty members. This study aims to achieve the following objectives:

1. To establish factors that have influence on behavioral intentions the acceptance of asynchronous virtual learning technologies by faculty members at Elmergib University.

http://www.doi.org/10.62341/fsaa0927

2. To establish factors that have influence on use behavior the acceptance of asynchronous virtual learning technologies by faculty members at Elmergib University.

2. Literature Review

2.1. Review of related literature about UTAUT2 and teachers

Many studies aimed to determine the origins in e-learning technologies application in accordance with the UTAUT2 model for teachers (e.g., Saunders-Wyndham, 2021; Tseng et al., 2022; W. Du & Liang, 2024). Raman and Don (2013) investigated the factors affecting the intention of pre service teachers' usage of the Learning Zone (Moodle). It is a learning management method used by teachers and students during learning-teaching process by the UTAUT2 model. The results revealed that hedonic expectancy and facilitating conditions were significant factors in predicting students' behavioral intentions. In addition, Saunders-Wyndham (2021) conducted a study to explore the perceptions of teachers regarding online learning during the first worldwide COVID-19 pandemic wave. It aimed to determine the extent to appropriately distinguish the factors that influence teachers' perception of teaching online by the UTAUT2 model. It was indicated that the UTAUT2 model showed a good fit with high internal reliability, though the strong correlation between variables indicates a degree of multi collinearity. Latent factor elements are considered as multilayered constructs that show multifaceted relationships within a teaching circumstance. Some recommendations that could enhance the development of online learning plan were provided. It informed practices that best represent online learning management; and reflect the socio-cultural beliefs of the teaching populations.
Arista and Abbas (2022) investigated performance of principals, and teachers; where teachers were given further tasks. Performance appraisals were necessary to assess the effectiveness of their work. The goal was to apply the UTAUT2 to determine the reason behind accepting the performance appraisal method by teachers. It was found that behavioral intention (BI) to employ the system is influenced by social influence (SI), facilitating conditions (FC), performance expectancy (PE), and habit (HT). System use behavior (UB) was also found to be influenced by behavioral intention (BI), facilitating conditions (FC), and habit (HT), and. Therefore, it is suggested focusing on enhancing the system's ease of use and minimizing the system's flow complexity in order to

http://www.doi.org/10.62341/fsaa0927

enhance the system's adoption. Tseng et al. (2022) attempted to determine the factors influencing teachers' application of massive online open courses (MOOCs) as an instructional delivery method according to the UTAUT2 model. It was found that the price value, social influence, facilitating conditions, and performance expectancy were the most factors affecting teachers' MOOCs usage intention.

Besides, Du and Liang (2024) investigated the predictors of usage intention of continued VR technology among elementary and secondary schools teachers in their learning process based on the UTAUT2 model. The results demonstrated that effort expectancy, performance expectancy, facilitating conditions, social influence, and hedonic motivation were the most significant factors impacted elementary and secondary.

Most of the previous about teachers' perception of online learning were carried out in different regions around the world and studies in Libyan context are very limited. El-Masri and Tarhini (2017) investigated the factors influencing students' adoption of online learning with trust as an additional variable to the UTAUT2 model. It was found that the proposed relationships vary across different educational contexts (developed vs. developing). Venkatesh et al. (2012) emphasized the need to test UTAUT2 in different countries, different technologies with different age groups. Hence, Libya was selected for this current study with members of university and asynchronous virtual learning technology used for teaching. Venkatesh et al. (2012) added hedonic motivation, habit, and price value as indicators based on key theoretical perspectives that complement the theoretical mechanisms in UTAUT. Moreover, Venkatesh et al. (2012) highlighted the significance of adding other relevant factors that could help increase the applicability of UTAUT to a wider range of consumer technology usage contexts. Consequently, the trust factor was added in this study.

Moreover, some current studies revealed that the UTAUT2 model is being employed to examine new technologies implemented into higher education context, such as tools of Artificial Intelligence (AI) (Xu, et al., 2024, Wattanakasiwich, et al., 2025), humanoid robots (Ates, et al., 2025). Therefore, this theoretical basis was chosen to build a proposal that explains the acceptance and usage of asynchronous virtual learning technologies by faculty members at universities.

http://www.doi.org/10.62341/fsaa0927

2.2. The Unified Theory of Acceptance and Use of Technology (UTAUT1) and the extension (UTAUT2)

The original UTAUT model combines multiple theories and models of individual acceptance and determinants of information technology acceptance. Venkatesh et al., (2003) reviewed the most prominent theories used to explain an individual's acceptance of technology, including: the social cognitive theory, the theory of planned behavior, the theory of reasoned action, the innovation diffusion theory, the motivational model, the technology acceptance model, a model combining the technology acceptance model, and the model of PC utilization.

The UTAUT identifies four elements as determinants of behavioural intention and the single construct of use behaviour. The constructs are defined as followed: (a) social influence (b) performance expectancy (c) effort expectancy (d) facilitating conditions (Venkatesh et al., 2003). Further studies revealed that age, gender, experience, and voluntariness are additional moderators for this causal relationship (Venkatesh et al., 2003; Venkatesh et al., 2012). The original UTAUT can be insufficient to predict the use and adoption of consumer IT since it was developed in the organizational context. Consequently, Venkatesh et al. (2012) proposed the UTAUT2 by adding additional constructs (i.e. hedonic motivation, price value, and habit). In addition to the construct relationships proposed in the original UTAUT, the following relationships were provided: first, behavioral intention can be determined by price value and hedonic motivation. Second, behavioral intention and usage behavior can be influenced by the habit. Third, behavioral intention can be affected by facilitating conditions. The proposed moderators in the UTAUT2 included age, gender, and experience (Venkatesh et al., 2012, p. 161).

2.3 The Proposed Model

The UTAUT2 model is extended in this study by integrating trust as a new concept, as presented in Figure 1. This framework examined the acceptance of asynchronous learning technologies and the level of user's awareness. The choice of this concept supports the practical consideration in the educational setting and consistent with accepted theoretical frameworks. Many studies examined the relationship between instructors and new technology, and the interplay between these two concepts has been investigated separately and collectively from different perspectives in the literature. Accordingly, the specific background and objectives of

http://www.doi.org/10.62341/fsaa0927

this study led to the selection of this external construct, derived from both related previous studies and research background.

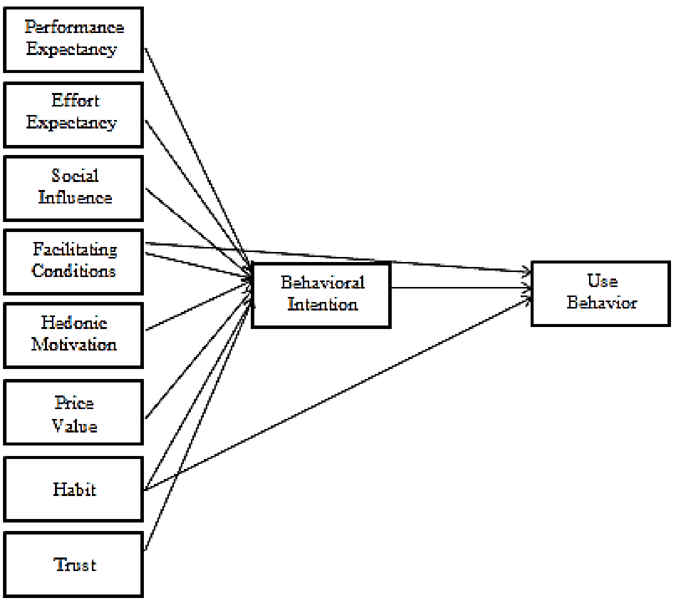

Figure 1, Research model

It is common that users are more likely to adopt a positive attitude towards any innovation if they trust in it to get helpful and accurate information. The positive attitude may increase the levels of usage and lead to intention to continue using it in the future. Moreover, trust may encourage users to share their private information with the system; this can further improve the accuracy and usefulness of its recommendations (Kim & Gambino, 2016).

2.4. Hypothesis development

This study developed hypotheses based on the UTAUT2 notion that price value, performance expectancy, social influence, effort expectancy, hedonic motivation, facilitating conditions, habit, and determine users' behavioral intention to adopt or use IT (Venkatesh et al., 2012). Furthermore, facilitating conditions and behavioral intention can facilitate IT use behavior. Since asynchronous virtual learning technologies are a type of educational technology, it is expected that the aforementioned relationships are applicable to asynchronous virtual learning technologies. Thus, the following hypotheses are formulated:

Performance Expectancy (PE) refers to the degree to which users

http://www.doi.org/10.62341/fsaa0927

trust that technology can enhance their job performance and working conditions (Venkatesh et al., 2003). It has been considered as one of the most influential factors in predicting Behavioral Intentions (BI) (Venkatesh et al., 2012). In the context of this study, PE can be defined as the extent to which university educators believe that using asynchronous virtual learning technologies will lead to improving teaching outcomes.

H1: Performance expectancy positively influences faculty members' behavioral intention to adopt asynchronous virtual learning technologies.

Effort Expectancy (EE) signifies the ease or difficulty with which users perceive the use of new technology (Venkatesh et al., 2003), and it stands as one of the most robust predictors of BI (Venkatesh et al., 2012). In the context of this study, EE can be characterized as the degree to which university educators believe that using asynchronous virtual learning technologies will not entail significant physical or mental exertion.

H2: Effort expectancy positively influences faculty members' behavioral intention to adopt asynchronous virtual learning technologies.

Social Influence (SI) represents the influence of individuals whom users consider important on their intention to use (Venkatesh et al., 2003). It is also regarded as one of the significant predictors of BI (Venkatesh et al., 2012). In this study, SI is defined as the opinions of other teachers, family members, and friends regarding the use of adopt asynchronous virtual learning technologies in teaching.

H3: Social influence positively influences behavioral intention of faculty members to adopt asynchronous virtual learning technologies.

Facilitating Conditions (FC) refers to users' perception of having sufficient awareness, trust, and technical resources to support the use of technology (Venkatesh et al., 2003). FC is also considered as one of the important factors influencing Behavioral Intentions (BI) (Venkatesh et al., 2012). In this study, FC are described as the extent to which university educators believe there are adequate organizational and technical foundations to support the use of adopt asynchronous virtual learning technologies in teaching.

H4: Facilitating conditions positively influence behavioral intention of faculty members to adopt asynchronous virtual learning technologies.

H5 Facilitating conditions positively influence use behavior

http://www.doi.org/10.62341/fsaa0927

intention of faculty members to adopt asynchronous virtual learning technologies.

Hedonic Motivation (HM) represents the enjoyment of users when using technology (Venkatesh et al., 2012). In this study, HM is described as the pleasure and enjoyment that university educators experience from using asynchronous virtual learning technologies.

H6: Hedonic motivation positively influences faculty members' behavioral intention to adopt asynchronous virtual learning technologies.

Price Value (PV) refers to the significant impact of costs and pricing structures associated with the use of technology (Venkatesh et al., 2012). In this study, PV is described as the costs incurred and the value generated by university educators from using asynchronous virtual learning technologies.

H7: Price value positively influences faculty members' behavioral intention to adopt asynchronous virtual learning technologies.

Habit (HB) assumes that past learning may influence people to perform actions automatically (Chopdar et al., 2018). Thus, habit is the user's perceived repeated behavioural patterns based on prior use of a technology (Venkatesh et al., 2012). In this study, it is expected that if university educators have more habitual behaviour towards using asynchronous virtual learning technologies, they are more probably to adopt it. Therefore, the following hypotheses are postulated:

H8: Habit positively influences faculty members' use behavior to adopt asynchronous virtual learning technologies.

H9: Habit positively influences faculty members' behavioral intention to adopt asynchronous virtual learning technologies.

Behavioral Intention (BI) is a pivotal factor within different intention models, recognized for its influence on the actual usage of technology (Venkatesh et al., 2003). In this study, BI is defined as the disposition of university educators toward integrating asynchronous virtual learning technologies into their teaching practices.

H10: Behavioral Intention has a positive effect on university educators use behavior to adopt asynchronous virtual learning technologies.

External constructs

Trust (TR) The trust variable indicates to an individual's perception that any system or technology can be depend on to achieve as proposed and protect their interests (Falcone & Castelfranchi,

http://www.doi.org/10.62341/fsaa0927

2001). Regarding the adoption and usage of technology, trust is a significant determinant of individuals' behavior (Kesharwani & Singh Bisht, 2012; El-Masri and Tarhini, 2017). In this study, trust is defined as university instructors' confidence to integrate and adopt asynchronous virtual learning technologies into their teaching practices.

H11: Trust positively influences behavioral intention of faculty members to adopt asynchronous virtual learning technologies.

3. Methodology

3.1 Survey Design

The statements used in this proposed research model were adapted from previous studies on UTAUT2 proposed by Venkatesh et al. (2012). It is designed for the adoption of e-learning and related work (e.g., El-Masri & Tarhini, 2017, Saunders-Wyndham, 2021; Zhang et al., 2021; Albayati, 2024; Tseng et al., 2022; Du & Liang, 2024). The questionnaire survey contained six items including demographic information (e.g. gender, academic major, academic qualification, academic degree, daily internet usage, and level of English proficiency), and 30 items related to the nine latent factors from the UTAUT2 model, in addition to the element of trust (see Appendix 1). Specifically, Behavioral Intention (BI), Social Influence (SI), Effort Expectancy (EE), Performance Expectancy (PE), Facilitating Conditions (FC), Price Value (PV), Hedonic Motivation (HM) and Habit (HB), were measured using three items, whereas Trust (TR) was measured using four items. Use Behavior (UB) was measured using two items. Answers were scaled using a five- point Likert scale: ranging from “strongly disagree=1” to “strongly agree=5”.

Before starting the survey officially, two educational experts were invited to examine the validity of the questionnaire. Based on their feedback, the questionnaire’s language and structure were modified and rewritten. Subsequently, the questionnaire was presented to a second expert-review round and reached agreement on the content. Also, prior to the implementation of the newly constructed scales for this study on the intended population, a pilot study was executed with 30 faculty members (15 females and 15 males) from the Elmergib University to evaluate their effectiveness. Discriminant validity was verified, and all constructs satisfied the reliability and validity requirements (Hair et al., 2013). Additionally, the study did not include any faculty members who took part in the pilot study.

http://www.doi.org/10.62341/fsaa0927

3.2 Participation and procedures

The study used a quantitative research method; with a questionnaire as a main instrument to collect the data from faculty members at Elmergib University. This is conducted by sending an email with a questionnaire to the target participants. Based on the rules of the ‘‘Google form’’ survey platform, incomplete questionnaires could not be submitted. All surveys were voluntary and anonymous, and the results of the survey were only used for the purpose of the study. To avoid data distortion, the researcher collated and verified the returned questionnaires based on the time of completion and whether they were characterized by regularity of completion. The invalid responses were excluded (e.g., overly regularized answers). The survey lasted from 10th June 2025 to 15th August 2025. Ultimately, 154 questionnaires were collected.

3.3 Data analysis method

The collected data was analyzed and presented through descriptive statistics via frequency and percentage. Moreover, the study used Structural Equation Modeling (SEM) to test the study hypotheses relating to the relationship between the variables with the help of SmartPLS4.1.1 Software.

The SEM analysis clarifies how users’ attitude and intention can be explained about the adoption of asynchronous virtual learning technologies through the UTAUT2 model. Moreover, this study investigates the role of some external variables on influencing users’ intention and attitudes.

The measurement models are the first focus of the PLS-SEM assessment model. The PLS-SEM estimation assessment helps researchers to assess the validity and reliability of the constructs. This study aims to evaluating the reflective measurement models because the association between the construct and its indicators is reflective (reflective measurement models). Hence, in this reflective model, the convergent validity, discriminate validity, and internal consistency reliability are determined. The coefficient of determination (R^2 value or R-square) is utilized to measure the structural models.

4. Results and discussion

4.1 Descriptive analysis

Table 1 presents the demographic characteristics of the participants. The results show that most of the participants (51 %) are males, whereas females constituted 49%. Regarding academic

http://www.doi.org/10.62341/fsaa0927

qualification, most respondents hold Master 73%, while 27 % hold a doctorate. As for their academic major, the majority of respondents are in applied sciences, making up 57% and 43 % were humanities Sciences. The academic degree distribution of the respondents was as follows: 25 % assistant lecture, 33% lecturer, 36% assistant professor, 3% associate professor and 3% professor. Many respondents spend between 2-3 hours daily internet usage, representing approximately 44%, while 18% reporting an hour or less of usage. Some respondents (38%) spend around 4 hours or more daily on internet. Furthermore, most of the participants were an intermediate level of English, representing approximately 58 %, while 28% were weak, and approximately 14% were at an excellent level.

Table 1: Demographic information of the respondents

Item	Values	Frequency	Percentage
Gender	Male	78	50.6%
	Female	76	49.4%
Academic qualification	Master	113	73.4%
	Phd	41	26.6%
Academic major	Applied sciences	87	56.5%
	Humanities sciences	67	43.5%
Academic degree	Assistant lecture	39	25.3%
	Lecturer	50	32.5%
	Assistant professor	56	36.4%
	Associate professor	04	2.6%
	Professor	05	3.2%
Daily internet usage	An hour or less	28	18.2%
	2-3 hours	67	43.5%
	4 hours or more	59	38.3%
Level of English proficiency	Weak	43	27.9%
	Middle	90	58.4%
	Excellent	21	13.6%

4.2 Measurement models

Regardless the normality assumption, the PLS-SEM may work successfully for complex models (many indicators and constructs).

http://www.doi.org/10.62341/fsaa0927

Therefore, it was employed in this study to estimate the important target constructs or key "driving" constructs. The path in PLS model consists of two components: A structural model and a measurement model. A stricture model is known as the inner model in PLS-SEM and it describes the relationship between latent variables. A measurement model is defined as the outer model in PLS-SEM) and it describes the relationship between the variables and their indicators (Hair et al., 2016).

4.3 Measurement models

4.3.1 Convergent validity

Convergent validity is evaluated using outer loadings and average variance extracted (AVE) values, as displayed in Table 2. It is demonstrated that every indicator has an AVE >0.5 and outer loadings >= 0.769. Therefore, nothing needs to be eliminated because all indicators meet the broad convergent validity standards.

Table 2:Outer loadings and average variance extracted (AVE)

Construct	Indicator	Outer loadings	Average variance extracted (AVE)
BI	**BI1**	0.793	0.705
	BI2	0.855	
	BI3	0.868	
EE	**EE1**	0.845	0.694
	EE2	0.769	
	EE3	0.882	
FC	**FC1**	0.921	0.805
	FC2	0.896	
	FC3	0.876	
HB	**HB1**	0.885	0.832
	HB2	0.932	
	HB3	0.918	
HM	**HM1**	0.884	0.818
	HM2	0.920	
	HM3	0.910	
PE	**PE1**	0.914	0.860
	PE2	0.929	
	PE3	0.939	
PV	**PV1**	0.944	0.813
	PV2	0.871	
	PV3	0.887	
SI	**SI1**	0.882	0.838
	SI2	0.925	
	SI3	0.939	

http://www.doi.org/10.62341/fsaa0927

TR	**TR1**	0.908	0.779
	TR2	0.917	
	TR3	0.918	
	TR4	0.781	
UB	**UB1**	0.949	0.922
	UB2	0.971	

4.3.2 Discriminant validity

This study uses the heterotrait–monotrait ratio of correlations (HTMT) and the Fornell–Larcker criterion to evaluate discriminant validity. All of the diagonal values enclosed in parenthesis (square root of AVE) are used in the Fornell-Larcker criterion. According to Table 3, each latent variable should have a value greater than the construct's highest correlation.

Table 3: Fornell-Larcker criterion

	BI	EE	FC	HB	HM	PE	PV	SI	TR	UB
BI	**0.84**									
EE	0.68	**0.83**								
FC	0.70	0.63	**0.88**							
HB	0.72	0.52	0.47	**0.91**						
HM	0.69	0.47	0.46	0.64	**0.91**					
PE	0.72	0.54	0.40	0.57	0.65	**0.93**				
PV	0.65	0.52	0.60	0.55	0.36	0.50	**0.90**			
SI	0.71	0.58	0.74	0.66	0.63	0.59	0.59	**0.91**		
TR	0.66	0.54	0.64	0.51	0.51	0.50	0.48	0.63	**0.88**	
UB	0.64	0.59	0.44	0.52	0.59	0.53	0.52	0.52	0.43	**0.96**

The heterotrait–monotrait ratio of correlations (HTMT), which was first presented by Henseler et al. (2015), is the recommended technique for analyzing discriminant validity in PLS-SEM. To guarantee discriminant validity, an HTMT threshold of.90 is advised, especially for conceptually similar constructs; for more

http://www.doi.org/10.62341/fsaa0927

different constructions, a threshold of.85 is more suitable. All of the results in Table 4 are below the.85, indicating strong discriminant validity.

Table 4

	BI	EE	FC	HB	HM	PE	PV	SI	TR
BI									
EE	0.848								
FC	0.841	0.744							
HB	0.833	0.604	0.510						
HM	0.799	0.550	0.498	0.679					
PE	0.843	0.626	0.443	0.616	0.716				
PV	0.759	0.597	0.668	0.616	0.388	0.536			
SI	0.837	0.678	0.837	0.724	0.695	0.641	0.66		
TR	0.769	0.628	0.707	0.542	0.553	0.538	0.52	0.68	
UB	0.733	0.698	0.482	0.549	0.634	0.572	0.55	0.57	0.46

4.3.3 Internal consistency reliability (Cronbach's alpha, composite reliability)

Composite reliability and Cronbach's Alpha values ought to be at least 0.7 (Hair et al., 2016). Cronbach's alpha > 0.70 and combined reliability >0.70 are displayed in Table 5. This indicates that the construct met the requirements for dependability and internal consistency.

Table 5: The Reliability test

Construct	Cronbach's alpha	Composite reliability
BI	0.789	0.790
EE	0.781	0.811
FC	0.879	0.885
HB	0.900	0.919
HM	0.891	0.919
PE	0.918	0.919

http://www.doi.org/10.62341/fsaa0927

PV	0.887	0.916
SI	0.904	0.909
TR	0.904	0.904
UB	0.917	0.969

4.4 Structural model assessment

Assessing the degree of variation in the dependent variables was part of the model evaluation process. The primary indicators for estimating the structural model were path coefficients and Rsquared (R^2) (Ringle et al., 2015).

Then, the co-efficient of determination (R^2) is analyzed to establish the exploratory power of each construct and the overall model. The R^2 value should range between 0 and 1; where the higher values indicate greater exploratory. The general rule of thumb indicates that if R^2 value is 0.25, it is considered weak, .50 it is moderate, and 0.75 is significant (Hair et al., 2011).

Figure 2 displays the results of the PLS-SEM analysis and standardized regression co-efficients implies that the relationship between the study variables and R^2 values are within the circle.

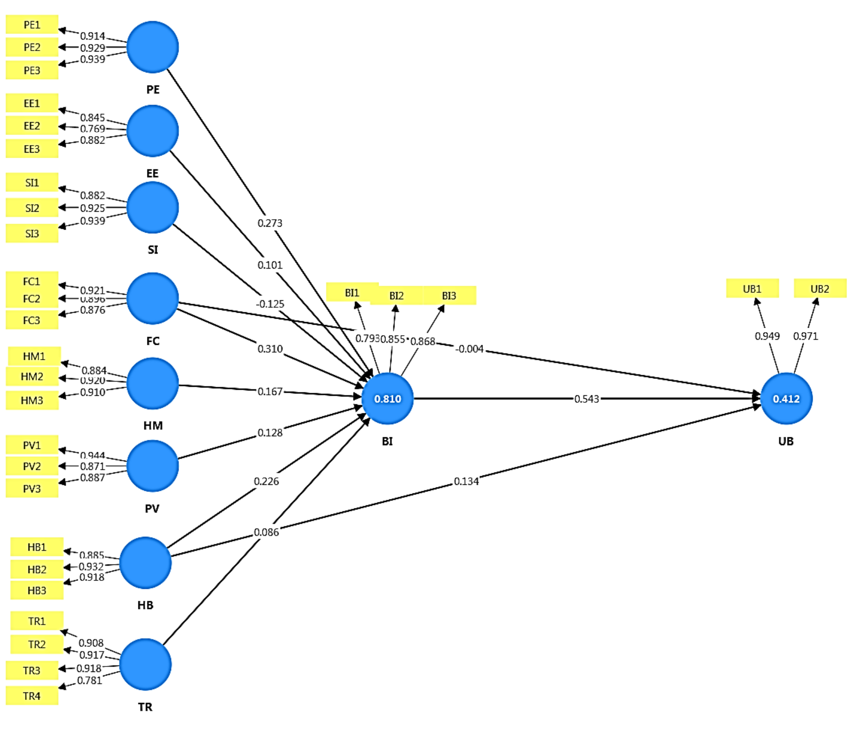

Figure 2, Path analysis

http://www.doi.org/10.62341/fsaa0927

From Figure 2, it can be observed that t the best predictor of "Behavioral intention" is "Facilitating Conditions" with a coefficient of .310, followed by "Performance expectancy" (.273), "Habit" (.226), "Hedonic Motivation" (0.167), and "Price Value" (0.128) which together explained 81% of the variance in "Behavioral intention. Positive effect on "Behavioral intention" is also observed for "Effort Expectancy" (. 101), and "Trust" (.086). However, this result shows that there is no statistical significant relationship. Conversely, "Behavioral intention" has the most significant impact (.543) on "Use behavior", accounting for 41.2% of the variance in "Use behavior". Positive effect on "Use behavior" is observed for "Habits" (.134). This result shows no statistical significant relationship.

Furthermore, the Path Coefficients (β) are fundamental measures at the inner model test stage for measuring the structural model. The path analysis was used to each hypothesis by estimating the path coefficient and p-value, as shown in Fig. 2 and Table 6.

Ghozali (2008) indicated that the greater the path coefficients, the more influential the variable is. Therefore, it can be concluded that behavioral intention (BI) is the most influential variable in this study with the value of 0.543. That is, the BI plays a dominant role in the adoption of the asynchronous virtual learning technologies in teaching.

In addition, the t-test step uses the bootstrapping method with a two-tailed test at this phase. This testing phase is necessary to determine whether the dependent variable is affected by the independent variable. The influence of variables is determined by the significance p value of the parameters coefficient with *t* statistical significance value (*t* table = 1.96) at a level of significance $p = 0.05$ for measurement paths (Priyatno, 2013).

Table 6: Hypotheses Results

Number of Hypotheses	Hypotheses	Path coefficients	T statistics (|O/STDEV|)	P values	Significance ($p < 0.05$)?
H1	**PE -> BI**	0.273	3.909	0.000	accepted
H2	**EE -> BI**	0.101	1.682	0.093	rejected
H3	**SI -> BI**	-0.125	1.855	0.064	rejected
H4:	**FC -> BI**	0.310	4.419	0.000	accepted
H5	**FC -> UB**	-0.004	0.027	0.978	rejected
H6	**HM -> BI**	0.167	2.859	0.004	accepted

http://www.doi.org/10.62341/fsaa0927

H7:	**PV -> BI**	0.128	2.205	0.028	accepted
H8	**HB -> UB**	0.134	1.502	0.133	rejected
H9	**HB -> BI**	0.226	3.639	0.000	accepted
H10	**BI -> UB**	0.543	3.737	0.000	accepted
H11	**TR -> BI**	0.086	1.521	0.128	Rejected

Hypothesis 1: (Path coefficients = 0.273, *p* value <.05): identifies the path between performance expectancy (PE) and behavioral intention (BI). This result shows that there is a significant relationship between performance expectancy (PE) and behavioral intention (BI). Specifically, it is observed that the faculty members are more possibly to adopt asynchronous virtual learning technologies in teaching when they have high levels of performance expectancy. Hence, the results of p-value (<.05) confirms that the relationship between PE and BI is statistically significant.
Hypothesis 2: (Path coefficients = 0.101, p value > .05) determines the relationship between Effort Expectancy (EE) and Behavioral Intention (BI). This result shows that effort expectancy had no influence on faculty members' behavioral intention to adopt asynchronous virtual learning technologies in teaching. Effort expectancy was conceptualized as the ease of use perceived by faculty members for using asynchronous virtual learning technologies in teaching. This reveals that some faculty members are not convinced of the significance of integrating educational technology into teaching methods. There is also a lack of incentive for faculty members to invest time and effort in introducing new technologies into the educational process.
Hypothesis 3: (Path coefficients = -0125, p value > .05) determines the relationship between social influence (SI) and behavioral intention (BI). The p value indicates that the relationship between SI and BI is not statistically significant. That is the social influence including colleagues and peers, does not influence the BI of faculty members to use and adopt asynchronous virtual learning technologies in teaching. Hence, it can be concluded that the SI is not a dominant factor in determining the BI to use asynchronous learning, as indicated by the high p value.
Hypothesis 4: (Path coefficients = 0.310, p value < .05): the relationship between facilitating conditions (FC) and behavioral

http://www.doi.org/10.62341/fsaa0927

intention (BI). This result shows that there is a significant relationship between FC and BI. Hence, it can be confirmed from the p- value the relationship between FC and BI is statistically significant.

Hypothesis 5: (Path coefficients =-0.004, p value > 0.05) describes the relationship between Facilitating Conditions (FC) and Use Behavior (UB). The result of p value demonstrates that there is no statistical significant relationship between facilitating conditions and use behavior. These findings suggest that faculty members did not find asynchronous virtual learning technologies interface easy to be used in teaching and it is not offered in other languages, requiring a lot of prompts to activate.

Hypothesis 6: (Path coefficients = 0.167, p value < 0.05): The path between Hedonic Motivation (HM) and Behavioral Intention (BI). This result shows that there is a significant relationship between hedonic motivation and behavioral intention. This finding indicates that the faculty members perceive asynchronous virtual learning technologies as enjoyable and entertaining in teaching. This could be attributed to the dialogue-based interface which interacts with people and allows different conversations within the boundaries set by the designers. Therefore, the p-value (< .05) shows that the relationship between HM and BI is statistically significant.

Hypothesis 7: (Path coefficients = 0.128, p value < .05): the relationship between price value (PV) and Behavioral Intention (BI) is mostly important and shows a significant relationship. Price value is a key factor influencing faculty members' behavioral intention to adopt and use asynchronous virtual learning technologies in teaching. Lecturers are more likely to use them if they believe their benefits outweigh their costs. The result of p-value (<.05) proves that the relationship between PV and BI is statistically significant.

Hypothesis 8: (Path coefficients = 0.134, p value > .05) determines the relationship between habit (HB) and use Behavior (UB). From this result, it can be concluded that there is no statistical relationship between habit and faculty members use behavior to adopt asynchronous virtual learning technologies in teaching.

Hypothesis 9: (Path coefficients = 0.226, p value < .05): the path between habit (HB) and Behavioral Intention (BI). This result shows that there is a significant relationship between habit and behavioral intention. This means that habit influences behavioral intention to adopt asynchronous virtual learning technologies at teaching. The results of this study indicate that participants believe that frequent

http://www.doi.org/10.62341/fsaa0927

and consistent use have an influence on their behavioral intention behavioral intention to adopt virtual learning asynchronous technologies at teaching. The result of p-vlaue (< .05) proves that the relationship between HB and BI is significant.
Hypothesis 10: (Path coefficients = 0.543, p value < 0.05): The path between Behavioral Intention (BI) and Use Behavior (UB) is very essential and reveals a significant relationship. Hence, it can be concluded that the relationship between BI and UB is particularly stronger than any other relationships within this model. It is found that behavioral intention, in particular, has a significant positive influence on the use intention to adopt asynchronous virtual learning technologies in teaching. Therefore, the result of p-value (<.05) revealed that this relationship is statistically significant.
Hypothesis 11: (Path coefficients = 0.086, p value >.05) defines the relationship between trust (TR) and behavioral intention (BI). The p-value result shows that there is no a statistical significant relationship between trust and behavioral intention. This means that faculty members did not have a high level of trust in their behavioral intention to adopt use asynchronous virtual learning technologies in teaching.
Additionally, in Table 5, the author runs another test, which tests the hypotheses using the T-Test, and the results showed that H1, H4, H6, H7, H9 and H10 are greater than or equal 1.96, leading to accept these hypotheses, and the values of H2, H3, H5, H8 and H11 are less than 1.96, which means the hypotheses are rejected. The p-value and path coefficients were used to support the same hypothesis

5. Conclusion

Based on the results of this study, it can be stated that universities can solve many challenges that occur in a classroom through the effective use of asynchronous virtual learning. Asynchronous virtual learning technologies support improved production monitoring and improving the skills, leading to enhancing the institutional performance and quality of production. The UTAUT2 model with the trust construct was applied with faculty members in the virtual asynchronous learning technologies in teaching at Elmergib University. With regard to the first research question, the results indicated that behavioral intention for faculty members to adopt asynchronous virtual learning technologies at Elmergib University highly depend on Performance Expectancy (PE), Hedonic Motivation (HM), Price Value (PV), Facilitating

http://www.doi.org/10.62341/fsaa0927

Conditions (FC), and Habit (HB) among the faculty members rather than Effort Expectancy (EE), Social Influence (SI) and Trust(TR). With regard to the second research question, the results indicated that actual use behavior to implement asynchronous virtual learning technologies at Elmergib University highly depend on Behavioral Intention (BI) to the faculty members rather Habit (HB) and Facilitating Conditions (FC).

The contribution of this study lies in better understanding the factors that play a vital role in adopting and utilizing technology at higher education context. It also provides valuable information for technology designers and marketers to consider every factor in designing and marketing of their products.

6. Recommendations:

From the discussion above and the research findings, the following strategy suggestions can be made for upcoming initiatives in the fields of asynchronous virtual learning technologies at Elmergib University:

1. One of the main motivators is performance expectations. Faculty members' perceptions of performance expectations and their adoption and utilization of virtual asynchronous learning technology should be improved by university management. Many lecturers have probably not embraced virtual asynchronous learning tools because they are unaware of the particular benefits of doing so. Therefore, university administrators should make sure that faculty members understand the advantages of utilizing virtual asynchronous learning tools. They can survey every faculty member who has taught utilizing e-learning for a long period and compile a list of advantages. The main advantages of using asynchronous virtual learning technology in university instruction can be communicated to faculty members.
2. Faculty members' behavioral desire to use virtual asynchronous learning technologies at universities is influenced by price value. Faculty members must be convinced by university officials that there are more advantages to using e-learning platforms than disadvantages. Although this will not be possible in the near future, university administrators must continuously explain the unique advantages of teaching with virtual asynchronous learning technologies and offer assistance to teachers in order to cut down on the time and effort needed to set them up and use them. Additionally, establish a free electronic library supported for

http://www.doi.org/10.62341/fsaa0927

students and faculty members and support programs and digital references for free via academic email, and the library should be available to all faculty members and students from 7 am to 9pm.

3. This study also showed that faculty members' behavioral intention to use virtual asynchronous learning technologies in the classroom is influenced by facilitating conditions. As a result, it is recommended that university administrator set up all the hardware and software required for faculty members and students to use e-learning services, as well as offer effective technical support for them in the event that they encounter issues with access, system failures, or service delays. Consequently, this will enhance how faculty members and students view the use of e-learning services.

4. Faculty members' behavioral intention to use virtual asynchronous learning technology at university is influenced by their habits. It is evident that those who utilize e-learning services more frequently engage in a more active learning process (Lewis et al. 2013). Therefore, university administrators should teach users, explain the advantages of e-learning services, and offer them both online and offline support until they become accustomed to using the technology as a significant component of their learning activities and experience. Faculty members are more likely to use the system when they develop a habit of using e-learning services.

5. Hedonic motivation has an influence on faculty members' behavioral intention to adopt virtual asynchronous learning technologies in teaching at university. The findings show that when using web-based learning platforms, users attain a respectable degree of intrinsic motivation. Thus, it is recommended that university administrators set up all the training resources required for faculty members and students to utilize e-learning services. Therefore, it is recommended that lecturers incorporate some enjoyable features into their lessons, such as games, films, and online tests that are very pertinent to the course material. This will allow users to feel free and joyful while utilizing the system. Additionally, web-based learning site developers and system designers should probably use strategies to lessen boredom and take advantage of learners' fun tendencies.

7.References

Albayati, H. (2024). Investigating undergraduate students' perceptions and awareness of using ChatGPT as a regular

http://www.doi.org/10.62341/fsaa0927

assistance tool: A user acceptance perspective study. Computers and Education: Artificial Intelligence, 6, 100203.

Arista, A., & Abbas, B. S. (2022). Using the UTAUT2 model to explain teacher acceptance of Work Performance Assessment System. International Journal of Evaluation and Research in Education (IJERE), 11(4), 2200 https://doi.org/10.11591/ijere.v11i4.22561.

Ates, H., & Polat, M. (2025). Exploring adoption of humanoid robots in education: UTAUT-2 and TOE models for science teachers. Education and Information Technologies, 1-42.

Bernard, R. M., Abrami, P. C., Lou, Y., Borokhovski, E., Wade, A., Wozney, L., et al. (2004). How does distance education compare with classroom instruction? A meta-analysis of the empirical literature. Rev. Educ. Res. 74, 379–439.doi: 10.3102/00346543074003379

Budiman, H. (2017). Peran Teknologi Informasi Dan Komunikasi Dalam Pendidikan. Al-Tadzkiyyah: Jurnal Pendidikan Islam, 8(1), 31. https://doi.org/10.24042/atjpi.v8i1.2095.

Bueno, D. C. (2020). G-SPACE's guidance on asynchronous teaching and learning via Google Classroom. April), 0–24.

Chopdar, P. K., Korfiatis, N., Sivakumar, V. J., & Lytras, M. D. (2018). Mobile shopping apps adoption and perceived risks: A cross-country perspective utilizing the Unified Theory of Acceptance and Use of Technology. Computers in Human Behavior, 86, 109–128.

Clark, R. C., and Mayer, R. E. (2016). E-Learning and the Science of Instruction: Proven Guidelines for Consumers and Designers of Multimedia Learning. Hoboken, New Jersey, US. John Wiley & Sons, Ltd.

Daniel, S. J. (2020). Education and the COVID-19 pandemic. Prospects, 49(1), 91-96

Dhawan, S. (2020). Online learning: A panacea in the time of COVID-19 crisis. Journal of Educational Technology Systems, 49(1), 5-22.

Du, W., & Liang, R. Y. (2024). Teachers' continued VR technology usage intention: An application of the UTAUT2 model. Sage Open, 14(1), 21582440231220112.

El-Masri, M., & Tarhini, A. (2017). Factors affecting the adoption of e-learning systems in Qatar and USA: Extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). Educational Technology Research and Development, 65, 743-

http://www.doi.org/10.62341/fsaa0927

763.
Falcone, R., & Castelfranchi, C. (2001). Social trust: A cognitive approach. In Trust and deception in virtual societies (pp. 55–90). Springer.
García-Peñalvo, F. J., & Corell, A. (2020). La COVID-19: enzima de la transformación digital de la docencia o reflejo de una crisis metodológica y competencial en la educación superior?. Campus virtuales, 9(2), 83-98.
García-Peñalvo, F. J. (2021). Avoiding the dark side of digital transformation in teaching. An institutional reference framework for eLearning in higher education. Sustainability, 13(4), 2023.
Ghozali, I. (2008). Structural Equation Modeling Metode Alternatif dengan Partial Least Square. Semarang: Badan Penerbit Universitas Diponegoro
Hair, J. F., Jr., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). A primer on partial least squares structural equation modeling (PLS-SEM). Sage publications
Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. Journal of Marketing Theory and Practice, 19(2), 139–152.https://doi.org/10.2753/MTP1069-6679190202
Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial least squares structural equation modeling: Rigorous applications,
better results and higher acceptance. Long Range Planning, 46, 1–12. https://doi.org/10.1016/j.lrp.2013.01.00
Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://doi.org/10. 1007/s11747-014-0403-8
Kesharwani, A., & Singh Bisht, S. (2012). The impact of trust and perceived risk on internet banking adoption in India: An extension of technology acceptance model. International Journal of Bank Marketing, 30(4), 303–322.
Khan, T. I., Kaewsaeng-on, R., & Saeed, I. (2019). Impact of workload on innovative performance: Moderating role of extrovert. Humanities & Social Sciences Reviews, 7(5), 123-133.
Kim, J., & Gambino, A. (2016). Do we trust the crowd or information system? Effects of personalization and bandwagon cues on users' attitudes and behavioral intentions toward a restaurant recommendation website. Computers in Human Behavior, 65, 369–379

http://www.doi.org/10.62341/fsaa0927

kistan, K., Malka, S., & Musni, M. (2020). The relationship between knowledge, attitude, and readiness of academic community in Covid-19 spread prevention: Batari Toja Nursing Academy, Watampone. International Journal of Health & Medical Sciences, 3(1), 72-78.

Lewis, C. C., Fretwell, Ch., Ryan, J., & Parham, J. B. (2013). Faculty use of established and emerging technologies in higher education: A unified theory of acceptance and use of technology perspective. International Journal of Higher Education, 2(2), 22–34.

Murphy, E., Rodríguez-Manzanares, M. A., and Barbour, M. (2011). Asynchronous and synchronous online teaching: perspectives of Canadian high school distance education teachers. Br. J. Educ. Technol. 42, 583–591. doi: 10.1111/j. 1467-8535.2010.01112.x

Murphy, M. P. (2020). COVID-19 and emergency eLearning: Consequences of the securitization of higher education for post-pandemic pedagogy. Contemporary security policy, 41(3), 492-505.

Panda, S. K. (2024). Analysis Of The Attitude Of Secondary School Teachers Towards The Use Of Bichronous Online Learning. MIER Journal of Educational Studies Trends and Practices, 119-131

Priyatno, D. (2013). Analisis korelasi, regresi, dan multivariate dengan SPSS. Yogyakarta: Gava Media.

Ramadan, K., Elatresh, J., Alzain, A., & Tokeser, U. (2020). Developing a new framework for understanding success/failure factors of e-learning implementation in Libya: Case Study; Misurata University.

Raman, A., & Don, Y. (2013). Preservice teachers' acceptance of learning management software: An application of the UTAUT2 model. International Education Studies, 6(7). https://doi.org/10.5539/ies.v6n7p157

Rapanta, C., Botturi, L., Goodyear, P., Guàrdia, L., & Koole, M. (2020). Online university teaching during and after the covid- 19 crisis: refocusing teacher presence and learning activity. Postdigital Science and Education, 2(3), 923–945. https:// doi.org/10.1007/s42438-020-00155-y

Ringle, C. M., Wende, S., & Becker, J.-M. (2015). SmartPLS 3. B onningstedt: SmartPLS. Retrieved July, 15, 2016.

http://www.doi.org/10.62341/fsaa0927

Tamilmani, K., Rana, N. P., & Dwivedi, Y. K. (2020). Consumer acceptance and use of information tech- nology: A meta-analytic evaluation of UTAUT2. Information Systems Frontiers, 1–19,. https://doi. org/10.1007/s10796-020-10007-6

Teo, T. (2014). Unpacking teachers' acceptance of technology: Tests of measurement invariance and latent mean differences. Computers and Education, 75, 127–135.
https://doi.org/10.1016/j. compedu.2014.01.014

Tseng, T. H., Lin, S., Wang, Y. S., & Liu, H. X. (2022). Investigating teachers' adoption of MOOCs: the perspective of UTAUT2. Interactive Learning Environments, 30(4), 635-650.

Saunders-Wyndham, J. . (2022) Teacher beliefs about online learning during COVID-19: an application of the UTAUT2 model (Doctoral dissertation, Macquarie University).

Suwaed, H. (2020). Choice Made from No Choice: Libyan EFL Students' Perceptions about Using Google Classroom for Learning Writing during COVID-19 Pandemic. International Journal of English Language & Translation Studies, 9(4), 56-62.

Vaca-Cárdenas, M. E., Ordoñez-Avila, E. R., Gabriele, L., & Vaca-Cárdenas, L. A. (2024). Asynchronous Virtual Education Acceptance of University Faculty During Covid-19. Journal of Ecohumanism, 3(3), 106-120.

Vallaster, C., & Sageder, M. (2020). Verändert Covid-19 die Akzeptanz virtueller Lehrformate in der Hochschulausbildung ?Implikationen für die Hochschulentwicklung [Does Covid-19 change the acceptance of virtual teaching formats in higher education? Implications for Higher Education Development]. Zeitschrift Für Hochschulentwicklung, 15(4), 281–301. https://doi.org/10.3217/zfhe-15-04/16

Venkatesh, Morris, Davis, & Davis. (2003). User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly, 27(3), 425. https://doi.org/10.2307/30036540

Venkatesh, Thong, & Xu. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 36(1), 157-178.https://doi.org/10.2307/41410412

Venkatesh, V., Thong, J., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. Journal of the Association for Information Systems, 17(5), 328- 376. https://doi.org/10.17705/1jais.00428

Wattanakasiwich, P., Kaewkhong, K., & Katwibun, D. (2025).

http://www.doi.org/10.62341/fsaa0927

Physics instructors' acceptance and implementation of generative AI. Physical Review Physics Education Research, 21(1), 010155.

Xie, H., Liu, W., Bhairma, J., and Shim, E. (2018). "Analysis of synchronous and asynchronous E-learning environments," in Proceedings of the 2018 3rd Joint International Information Technology, Mechanical and Electronic Engineering Conference (JIMEC 2018), ed. B. Xu (Paris: Atlantis Press).

Xu, S., Chen, P., & Zhang, G. (2024). Exploring Chinese University Educators' Acceptance and Intention to use AI tools: An application of the UTAUT2 model. SAGE Open, 14(4), 21582440241290013.

Yanjun, G. A. O., WONG, S. L., & KHAMBARI, M. N. M. (2021, November). Predictors of English as a Foreign Language (EFL) Teachers' Acceptance of Online Teaching in Higher Education Institutions in China. In International Conference on Computers in Education.

Zhang, Y. B., Zhang, L. L., & Kim, H. K. (2021). The effect of UTAUT2 on use intention and use behavior in online learning platform. *Journal of Logistics, Informatics and Service Science*, *8*(1), 67-81.

Zulfitria, Ansharullah, & Fadhillah, R. (2020). Penggunaan Teknologi & Internet sebagai Media.

8.Appendex1

Construct	**Item**	**The Question**
Performance Expectancy (PE)	PE1	-I find asynchronous virtual learning technologies useful in my daily work life as an educator..
	PE2	-Using asynchronous virtual learning technologies helps me accomplish lesson preparation more quickly.
	PE3	-Using asynchronous virtual learning technologies increases my productivity regarding lessons.
	EE1	Learning how to use asynchronous virtual learning technologies for the classroom is easy for me.

http://www.doi.org/10.62341/fsaa0927

Effort Expectancy (EE)	EE2	My interaction with asynchronous virtual learning technologies in teaching is clear and understandable.
	EE3	I find asynchronous virtual learning technologies in education easy to use.
Social Influence (SI)	SI1	-Co-workers who are important to me think that I should use asynchronous virtual learning technologies in my teaching.
	SI2	-Co-workers who influence my behaviour think that I should use asynchronous virtual learning technologies in my teaching.
	SI3	-Co-workers whose opinions that I value prefer that I use asynchronous virtual learning technologies in lessons.
Facilitating Conditions (FC)	FC1	I have the means necessary to use asynchronous virtual learning technologies in my teaching.
	FC2	I have the knowledge necessary to use asynchronous virtual learning technologies in my lessons.
	FC3	-Online resources are compatible with technologies I use for the classroom.
Habit (HB)	HB1	-The use of asynchronous virtual learning technology in teaching has become a habit for me.
	HB2	-I am dependent on using asynchronous virtual learning technologies in my teaching.
	HB3	-I must use asynchronous virtual learning technologies in my teaching.
Hedonic Motivation (HM)	HM 1	Asynchronous virtual learning technologies provide an engaging learning environment.
	HM 2	I like using Asynchronous virtual learning technologies in my teaching.
	HM 3	It is fun to use Asynchronous virtual learning technologies in my teaching.
Price Value (PV)	PV1	Asynchronous virtual learning technologies used in education are reasonably priced.
	PV2	- Asynchronous virtual learning technologies used in education are a good value for the money.

http://www.doi.org/10.62341/fsaa0927

	PV3	At the current price, Asynchronous virtual learning technologies provide a good value for educational needs.
Trust(TR)	TR1	I think that asynchronous virtual learning technologies are effective and secure in what it is designed to do.
	TR2	I feel assured that legal and technological structures adequately protect me from problems on asynchronous virtual learning technologies .
	TR3	I think that asynchronous virtual learning technologies users are trustworthy
	TR4	I think that asynchronous virtual learning technologies are made in a trusted organization.
Behavioral Intention (BI)	BI1	I intend to continue using asynchronous virtual learning technologies to teach in the future.
	BI2	I always try to use asynchronous virtual learning technologies in my daily work life
	BI3	I plan to continue to use asynchronous virtual learning technologies frequently in my teaching after the COVID-19 situation is resolved
Use Behavior (UB)	UB1	I am actually utilizing the asynchronous virtual learning technologies platform and want to continue to use it.
	UB2	- I use the asynchronous virtual learning technologies whenever I need them.