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THE EFFECT OF HUMAN-COMPUTER INTERACTION (HCI) FACTORS ON STUDENTS' E-LEARNING ACCEPTANCE AND SUCCESS DURING COVID-19 PANDEMIC

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APPROVAL

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In addition, I acknowledge that any claim of irregularity that may arise in relation to this work will result in a disciplinary action in accordance with the university legislation.

Fareed AL-Sayid

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24/09/2022

This thesis work is dedicated to my dear wife, Rajaa Budair, who has been a constant source of encouragement and support during the challenges of studying and life. This work is also dedicated to the soul of my father, and to my great mother, who has taught me to work hard for the things that I aspire to achieve.

Also, I dedicate this thesis to my best friends, beloved children, precious brothers and sisters, and all the people in my life who touch my heart.

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THE EFFECT OF HUMAN-COMPUTER INTERACTION (HCI) FACTORS ON STUDENTS' E-LEARNING ACCEPTANCE AND SUCCESS DURING COVID-19 PANDEMIC

ABSTRACT

The purpose of this study is to investigate the effect of human-computer interaction (HCI) factors on the ease of use and usefulness of e-learning and their success (SS) at the time of the COVID-19 pandemic, to investigate if students' activities on systems moderate the relationship between the main constructs in the proposed model called "e-LASS," which goes beyond technology adoption, and to explore non-linear relationships between these constructs. Moreover, this study proposes a comprehensive model called "e-LASS2," integrating the main (Technology Acceptance Model- TAM) factors included in e-LASS and a unified theory of acceptance and use of technology (UTAUT) factors. To answer the questions that addressed these relations in the first and second parts, the researcher surveyed 103 students from Kadir Has University whose grade and activity logs were accessible, while the data related to the third part were collected via an online survey conducted on 232 students utilizing the Khas Learn system of Kadir Has University in Turkey. The results of the first and second parts show that most of the hypotheses have been proven, three comprehensive conceptual models were developed, the grades in the online courses improved students' GPA, and the logs moderate the effects of HCI on TAM which together explained 54.9% of the variance in SS (student success), usefulness is the strongest determinant of SS, and non-linear models (cubic, quadratic, logarithmic, and s-curve) performed better in the description for the correlations when compared to linear models. The findings of the integrative approach in the third part reveal that the main predictors of students' success are behavior intention, ease of use, usefulness, visual design, and learner interface interactivity which explained 53.6% of perceived success in using the system.

Keywords: Human-Computer Interaction, Student's Success, Technology Acceptance, Interactivity, Collaborative Learning, Non-Linearity, Grounded Theory, Self-Efficacy

COVID-19 PANDEMİSİ SIRASINDA İNSAN-BILGISAYAR ETKILEŞIMI (HCI) FAKTÖRLERİNİN ÖĞRENCİLERİN ELEKTRONİK ÖĞRENİMİ BENİMSEME VE BAŞARISI ÜZERİNE ETKİSİ

ÖZET

Bu çalışmanın amacı, COVID-19 salgını sırasında insan-bilgisayar etkileşimi (HCI) faktörlerinin elektronik öğrenmenin kullanım kolaylığı, kullanışlılığı ve başarısı (SS) üzerindeki etkisini; öğrencilerin sistemler üzerindeki etkinliklerinin teknolojinin benimsenmesinin ötesine geçen "e-LASS" olarak adlandırılan önerilen modeldeki ana yapılar arasındaki ilişkiyi yönetip yönetmediğini; ve bu yapılar arasındaki doğrusal olmayan ilişkileri araştırmaktır. Ayrıca, bu çalışmada e-LASS'ta yer alan ana (Teknoloji Kabul Modeli- TAM) faktörleri ve birleşik bir teknoloji kabulü ve kullanımı teorisi (UTAUT) faktörlerini entegre eden "e-LASS2" adlı kapsamlı bir model önerilmiştir. Birinci ve ikinci bölümlerde bu ilişkileri ele alan soruları yanıtlamak için araştırmacı, Kadir Has Üniversitesi'nden not ve etkinlik kayıtlarına ulaşılabilen 103 öğrenciye anket uygulamıştır. Üçüncü bölüme ilişkin veriler ise Kadir Has Üniversitesi'nin Khas Learn sisteminden yararlanan 232 öğrenci üzerinde yapılan çevrimiçi anket yoluyla toplanmıştır. Birinci ve ikinci bölümlerin sonuçları, hipotezlerin çoğunun kanıtlandığını, üç kapsamlı kavramsal modelin geliştirildiğini, çevrimiçi derslerdeki notların öğrencilerin genel not ortalamasını iyileştirdiğini ve sayfa ziyaretlerinin HCI'nin TAM üzerindeki etkilerini arttırdığını ve bunların birlikte %54.9'unu açıkladığını göstermektedir. Kullanışlılık, öğrenci başarısı (SS)'daki varyansın en güçlü belirleyicisidir ve doğrusal olmayan modeller (kübik, ikinci dereceden, logaritmik ve s-eğrisi), doğrusal modellere kıyasla korelasyonların açıklamasında daha iyi performans göstermiştir. Üçüncü bölümdeki bütünleştirici yaklaşımın bulguları, öğrencilerin başarısının temel etkileyicilerinin davranış niyeti, kullanım kolaylığı, kullanışlılık, görsel tasarım ve sistemi kullanmada algılanan başarının %53.6'sını açıklayan öğrenen arayüzü etkileşimi olduğunu ortaya koymaktadır.

Anahtar Sözcükler: İnsan-Bilgisayar Etkileşimi, Öğrencinin Başarısı, Teknoloji Kabulü, Etkileşim, Işbirlikçi Öğrenme, Doğrusal Olmama, Kuram Oluşturma, Öz Yeterlilik

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LIST OF SYMBOLS

b	Represents the Coefficients of the Moderation Model
d	Cohen's d (represents the effect size, based on t-Test for equality of means)
Logs	Students' Activity via Web-Based System
R or *r*	Coefficient of Correlation
R^2	Coefficient of Determination
β	Coefficients of the Mediation Model
η^2	Eta-square (represents the effect size, based on One-Way ANOVA test)
ρ	Pearson Correlation (represents the coefficient of correlation)

LIST OF ACRONMYMS AND ABBREVIATIONS

AcS	Accessibility and Technical Support
BI	Behaviour Intention
CE	Course Environment
CES	Course Evaluation System
CQ	Content Quality
CSC	Course Structure and Content
ECTS	Attained Number of Credits
EE	Effort Expectancy
e-LASS	E-Learning Acceptance and Students' Success
e-LASS2	E-Learning Acceptance and Students' Success (second version of e-LASS)
EMIS	Education Management Information Systems
EoU	Perceived Ease of Use
FC	Facilitating Conditions
GPA	Grade Point Average
GT	Grounded Theory
HCI	Human-Computer Interaction
ICT	Information and Communications Technology
IDT	Innovation Diffusion Theory
IS	Information System
IT	Information Technology
KMO	Kaiser-Meyer-Olkin (sample adequacy)
LInt	Learner-Interface Interactivity
LSD	Least Significant Difference
MM	Motivational Model
Moodle	Modular Object-Oriented Dynamic Learning Environment
MPCU	Model of PC Utilization
Nav	Navigation
SCT	Social Cognitive Theory
SE	Self-Efficacy
SEE	Standard Error of Estimate
SQ	System Quality

SS	Students’ Success
TAM	Technology Acceptance Model
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
U	Perceived Usefulness
UTAUT	Unified Theory of Acceptance and Use of Technology
VD	Visual Design

1. INTRODUCTION

With the rapid growth of e-technology market worldwide, which has become very important in all aspects of our life, there is a need to increase the users' percentage, and also enhance their perceptions toward any technology based-computer application through developing human-computer interaction (HCI).

Since the beginning of 2020, the world's exposure to the outbreak and negative effects of the COVID-19 pandemic led to unprecedented lockdown measures, including the closure of universities, schools, and workplaces. Because of these precautions, and the retreat from face-to-face traditional education of physical classroom, countries have expanded the uncharacteristic scope of e-learning (Bozkurt et al., 2020). As a result of this circumstance, there is a need to enhance user engagement.

Likewise, Turkish universities have transitioned to e-learning, although online learning is not a new technique or method delivered in such universities, after their preparations and completion for online teaching platforms and tools. However, the students and instructors did not have an opportunity or adequate time to orient themselves to a series of platforms. Web-based education policies were implemented individually by their universities (Bozkurt & Sharma, 2020).

Web-based learning is a distance education system, which is based on ICT with a web interface and can be classified based on the level of interactivity, whereas related models can include all of the collaborative and interactive learning conditions found in face-to-face learning in the classroom (Laipaka & Sarwoko, 2011). Recently, web-based learning has become a great resource for collaborative learning between students and their teachers or peers where students can access, receive, or share information via the internet without the limitations of environment or time. A platform offers potential facilities and flexible interactive learning although its resources are exhausted and not actively facilitated or operational in some educational institutions (Iyamuremye et al., 2022). Furthermore, web-based learning systems can play a critical role in supporting learning via a pervasive digital environment that is equipped with interactive tools such as wikis, blogs, discussion platforms, and chat rooms, which require learners to be digitally and technically literate (Alotumi, 2022).

E-learning platforms which employ hypertext and hypermedia to allow several subjects to be linked with each other in different ways, are used extensively in education. In addition, they provide links for facilitating browsing, and introduce a map that provides an overall view of the information for direct navigation and access to the various necessary knowledge. This requires computer-assisted learning and web-assisted course materials. The users may lose motivation to benefit from the capabilities of web-based learning if it does not match the actual requirements of the tasks or duties that they seek to implement (Rozanski & Haake, 2017). In addition, it is important to ensure that the e-learning environment accommodates the needs of users due to the development of information technology, which has allowed them to access instructional materials anywhere, any time. So, to address each learner's preferences, it is necessary to consider human factors in the process of e-learning environments' development (Chen et al., 2019).

Furthermore, e-learning depends on the computer in preparing and presenting educational content, which appears in several forms, including web-based learning, collaborated learning, and virtual learning. This is what makes the search for e-learning problems in the context of sociological, psychological, cognitive, and attitude based model relatively new (Khamparia & Pandey, 2020). Most of the studies in the literature associated with web-based learning systems were primarily concerned with the e-learning acceptance and the enhancement of the actual use of these systems by users. This requires an understanding of the factors that influence behavioural intention to use these systems (Calisir et al., 2014), under the complex nature of users' perceptions and their characteristics or levels.

Moreover, the success of e-learning systems is governed by interactive learning, a domain ruled by learner-learner interactions, learner-teacher interactions (Jalal & Mahmood, 2019), and learner-interface interactions. However, published reports indicate that educational activities, which promote interactivity, were generally absent from collaborative and participatory learning throughout the COVID-19 pandemic period. It is confirmed by some statistics that 96% of users believe they have not been exposed to interactive learning via the web, which explains why two-thirds of the students prefer interactive learning in the classrooms to web-based learning platforms (Rabayah & Amira, 2022). But this perception of the students is contradicted by the scholars who demonstrated the advanced effectiveness of online collaborative learning compared to face-to-face learning. Also, they added that interactive online websites and their tools, services, and activities that support collaboration contribute to enhancing learning outcomes as well as the psychological well-being of students, in terms of helping share information and resources, link with others, exchange ideas, build professional personas, engage in social commentary, offer guidance to others, and highlight their achievement and engagement in different online networks (Alalwan, 2022). It is clear from previous studies that the focus is based on the opinion of scientists and the negative impression by students, and this requires verification of the impact of interactive activities via the internet and computer use, but from the students' point of view, on their achievement and perceived success.

Most of the research concerned with the acceptance of e-learning focuses on users' characteristics while a few covered the system and computer's characteristics, in terms of interactivity, interface design, and the effect of interaction on behaviours and perceptions, besides technical matters and online content. These match what Lewis and Mack (1982) figured out earlier that step-by-step instructions are not quite as fit because learners could read them differently from the designer's intentions (Lewis & Mack, 1982). Although it was believed that a proper design of the interactive system makes users need no or little aid or training, it is an ideal view of the reality of e-learning even with the best systems currently available according to Rozanski and Haake (2017), who described the computer as a complex device, with which it is necessary to assist the user through an adaptive system, designed to allow greater flexibility and interactivity presented in different times or situations, and to design this assistance in the system properly (Rozanski & Haake, 2017).

In addition, researchers have recently focused on critical post-adoption factors and the influential perceived learning criteria and satisfaction to assess the e-learning system's effectiveness. Perceived learning from endogenous constructs used as normative variables in a higher education context, which were classified under four broad groups, according to Yunusa and Umar (2021) can listed as follows: (i) Communication dynamics such as information quality, communicativeness, and interaction: student-content, student-technology, student-student, and learner-interface; (ii) E-learning environmental factors such as course structure, course evaluation, course responsiveness, ease of navigation, ease of use, ease of access, usefulness, content completeness, and content currency; (iii) Organizational factors such as system quality, system functionality, service quality, technological support, and university support and services; (iv) Finally, personality and situational factors such as self-efficacy, student characteristics, personal innovativeness, ability to comprehend, age, gender, performance expectation, internet-based skills, and learner dimensions: life competence, engagement, skill achievement, experience. These constructs were extracted by the researchers upon a review of 53 articles that they assume will provide a valuable overview of reference materials that may guide future research. Furthermore, the researchers pointed out the importance of perceived learning outcomes as a measure of student's learning achievement as grades, performance, or the achievements as reported by the learners at the end of the learning experience, which is one of the most important indicators of the success of the system and educational process (Yunusa & Umar, 2021). To improve any system facilities and technology in terms of safety, utility, efficiency, functionality, interactivity, and usability, associated with users' necessities, the decision-makers and engineering designers should consider human-computer interaction (HCI) factors as they have a major role in process development of collaborative learning carried out through online platforms. Sharma and Alvi (2021) stated that there is a relationship between perceived online learning in higher education and learners' computer knowledge, lack of awareness, personal touch, interest, and interaction due to connectivity issues.

HCI becomes a core aspect of any system-based-technology development process to satisfy users' needs and to improve system facilities, which confirm if the system is safe, useful, effective, efficient, easy to learn, and easy to use and satisfactory. Hornbæk and Hertzum (2017) argue that the technology acceptance models do not model the actions of users on specific occasions, same as their original models focusing on rational behaviour like regularities in behaviour, response tendencies, and consistent patterns of action. Therefore, in the context of human-computer interaction, it is very important to incorporate users' experiences with their emotions and perceptions, which constitute the social aspect, because these constructs are common in the practical use and adoption of the system. However, the systems' features are necessary when they are linked with the actual usage of competing systems. Moreover, accounting users' activities seem very important because they probably moderate the effects of the constructs in the models (Hornbæk & Hertzum, 2017).

Different studies have investigated students’ experiences in web-based learning in terms of attitudes or technical issues. But few studies merely focus on the effect of human-computer interaction on the student's acceptance of e-learning technology, and thus student success, and if their activities moderate some of those relationships during the online learning process. From these points of view, it was necessary to integrate the constructs of the HCI with the constructs of technology acceptance in the model of this study, and to test the extent to which the learner's perceptions affect their perceived success.

The research’s novelty lies in its aim of constructing a conceptual model that predicts the effect of the users' activities and the perceived system characteristics, as a result of their interaction with the computer, on the acceptance of e-learning in the context of perceived success, and in light of the actual use of the system which was imposed by the presence of the COVID-19 pandemic. This goes beyond technology adoption. So, the main objective of this study is to propose a conceptual model that explores the extent to which students' activities on the web moderate the relationship between factors related to HCI, e-learning acceptance, and students’ success if these relationships are proven.

Furthermore, most of the previous studies have investigated the linear relationships between two theories related to either technology acceptance as a dependent variable or extended factors as the independent variables within a model. However, formulating accurate non-linear models provides a powerful heuristic to predict the detailed causal effects (Bervell & Umar, 2017).

When bearing in mind non-linear connections rather than linearity in technology adoption models, the use of non-linear postulates in analysis has the potential to reduce the exaggeration or misjudgeement of the most important impact for the results of the linear presumption; avoid the incorrect, incomplete, or partial explanation of the outcomes caused by linearity clarification (Titah & Barki, 2009); earn probable opportunities to be aware of the difficult relationship between the constructs of technology acceptance models; discover the complex and emergency relationship that the original theory suggested between the constructs; and introduce better-detailed information about the relationship that exists between the two types of variables (independent and dependent) (Salim et al., 2015). Moreover, in comparison to linear analysis, this kind of model that uses a non-linear relationship can introduce a finer explanation power than the one followed by the common linear method where it maximizes the magnitudes of effect size and β (Rondan-Cataluña et al., 2015); helps offer a better understanding of the behaviour of the constructs (in particular, the linear relationship) in the model, which represents the slopes at threshold points on the curve of nonlinearity; hence it presents high segments of specific path coefficients that have the potential of grossly underestimated (Bervell & Umar, 2017). The effects may be negative or positive depending on the direction of those slopes, in contrast to the linear assumptions and interpretations that reversed the direction of influence. Kock (2016) argues that nonlinearity helps reach the findings that obviously differ from their linear results. Furthermore, it gives an adequate model and prediction that is better than linear models for predicting technology adoption, where more complex non-linear integrating effects are captured through behavioural decisions (Aloqaily et al., 2019).

Therefore, employing analytical approaches or methods that support nonlinearity may provide alternative interpretations that are crucial to different contexts associated with technology acceptance models without overstating or understating the main effects (Salim et al., 2015).

There are many motivations for conducting this study. First, we aim to predict the effect of human-computer interaction factors on collaborative web-based learning acceptance. Second, we want to investigate the relationship between all the proposed model constructs and the perceived learning outcomes with dependent variables like student grades or GPAs. Third, most previous research on technology acceptance used a linear model analysis to investigate major related factors or drivers. However, these single step analyses are insufficient to explain the complex nature of user perceptions and the sophisticated links that exist between constructs which represent the complexity of decision-making challenges in the real world. It requires carefully comparing the non-linear regression models to overcome these issues as a supplement, with higher accuracy, to linear models (Akgül & Osman, 2022). Finally, introducing a non-linear conceptual model may help researchers explain and even capture or prove more sophisticated causal relationships between factors.

So, this study aimed to provide a conceptual model, which explores the non-linearity relationships between HCI main factors and the ease of use and the usefulness of the collaborative learning. In this regard, the formations of linear and non-linear effects were selected, and the parameters of all variables were imported in SPSS-v25 software to derive the correlations; and then they were justified to see which can be a proper one based on the coefficient of determination and correlation values.

To accomplish the purposes of this study, it is organized into five chapters. Following the introduction; Chapter 2 covers a literature review associated with the technology acceptance models, studies conducted on e-learning adoption and students' success, and HCI main factors; Chapter 3 goes over the theoretical framework related to the impact of HCI and technology acceptance on students' success, and the effect of students' activities as a moderator; Chapter 4, develops a conceptual model for predicting the non-linear relationships between the first model's main constructs; Chapter 5, covers the effects of integrating TAM/UTAUT factors on students' intention to continue using e-learning and their perceived success. In each last three chapters, the researcher presents a general problem statement and objectives, hypotheses development, survey's structure and quality, study methods, analysis and findings, discussion of the results and some related implications, and finally include the conclusions.

2. LITERATURE REVIEW

Literature was reviewed to address the primary research question, which concerns theories of HCI main factors, e-learning acceptance, ease of use, usefulness, and non-linearity relationship. The following sections provide some background on these issues.

2.1 Non-linearity

Evidence has emerged indicating that the judgment function related to the latent psychological constructs of overt responses is affected by contextual effects of choice of anchors and stimulus spacing (Poulton, 1979). Also, effect sizes, smaller than the number of respondents in Likert scale, are affected by more contextual clues (Russell & Bobko, 1992). Busemeyer and Jones (1983) showed an inability to explain the moderated regression results when tracing the relationships between the latent variables and the observed variables that follow some unknown nonlinear monotonous functions, measured by Likert scale. They added using Likert scales in a number of subjects, which yielded effect sizes higher than expected. This is due to individual difference variables or other unknown contextual influences that may distort response functions, and this has been ignored in the applied settings despite its importance. According to Russell and Bobko (1992), the decision to use the Likert scale by researchers may force the respondents' outcomes to be represented in nonlinear response functions. The effect of nonlinearity highlights the detectability of true interaction effects (Busemeyer & Jones, 1983).

In addition, most relationships between constructs in social studies are nonlinear, such as information systems, where correlations between variables related to the behaviour of individuals are not necessarily linear (Cariou et al., 2014; Rondan-Cataluña et al., 2015). Although nonlinearities are predicted in behavioural and social studies related to information systems, these techniques are rarely used in such analysis of mainstream researchers in the field of IS. Most focus on linear assumptions and related techniques in testing relationships between variables and factors, while there are very few or scarce exceptions where researchers have relaxed the linear assumptions by reference to the original theoretical assumptions in their studies, which are also far between. Furthermore, the theoretical models employed in technology acceptance research have been mainly adopted from sociology and psychology theories. And mainstream research using technology adoption constructs such as perceived behavioural control, subjective norms, and attitudes have predominantly followed linearity assumptions despite the theories that suggest non-linear relationships with technology acceptance (Rodger & Gonzalez, 2014). This was confirmed by Liébana-Cabanillas et al. (2017), who considered that one of the main drawbacks is the use of traditional statistical techniques in the processes of predicting the behaviour of individuals, including the factors of perceived ease of use and perceived usefulness, which impose linearity between variables, where they used a different technique to model the complex non-linear relationships between the constructs.

Sharma et al. (2017) highlighted that TAM-based models have attracted the attention of most researchers as they are effective in creating causal explanatory models between independent and dependent factors, while they confirmed the need to be careful in using these models to predict user behaviour in terms of new technology. It needs different models that may often require the use of non-linear statistical methods due to the complex nature of users' perceptions concerning the adoption of new technologies.

One of the disadvantages of linear assumptions is that they present a risk of overstating or underestimating the main effects, as well as hindering potential opportunities to understand the complex relationships that exist between constructs of technology acceptance models, which could lead to erroneous, partial, or incomplete interpretations of the results (Titah & Barki, 2009; Salim et al., 2015). Furthermore, the attempts to estimate the real coefficients of nonlinearity, using estimated coefficients of linearity, lead to inconsistent and biased estimates of the models (Rondan-Cataluña et al., 2015).

There are many advantages to using nonlinearity in models related to technology acceptance. The magnitudes of effect size and β consistently increase when considering non-linear relationships compared to considering linearity in technology acceptance models (Rondan-Cataluña et al., 2015). Furthermore, using nonlinearity-based models tend to produce specific path coefficients in the higher parts that are likely to be underestimated. This helps provide a solid foundation that enables a better understanding of variable relationships based on the results of pathway relationships, and accordingly, appropriate decisions are made (Kock, 2016). For example, Habahbeh et al. (2018) study showed that some constructs of technology acceptance models exert a positive and negative non-linear effect on the dependent variable, depending on whether the perceived level is high or low. Among these constructs is perceived usefulness, which was proven by the nonlinearity test to have a positive effect on the behavioural intention to use the technology related to CloudERP when the perceived usefulness is high among respondents, while it has a negative effect on the behavioural intention to use this technology if perceived usefulness is low.

Moreover, in some cases related to the acceptance of technology like a UTAUT model, some constructs such as social influence SI, which is important for implementers of new technologies in decision-making, may not be significant in the linear regression test, while they are explained by the results of nonlinear relationships as proven by Bervell and Umar (2017).

Aloqaily et al. (2019) added that the nonlinear models generate a more appropriate forecast to interpret the results than the linear analysis, as it is can capture more complex effects and take the form of nonlinearity in the relationships between the components of technology acceptance, which are not all based on linearity, as they pointed out in behavioural intention decisions.

Prom et al. (2022) pointed out that the assumption of linearity in some social relations often leads to a misestimating of the effect of some independent factors on the dependent factors. And this may reflect a relationship from a negative to a positive effect at a specific level or feature in the independent variable, such as the effect of level of social features (low, medium, high), if the improvement is made, with a sufficient increase in satisfaction and attitude toward contribution. The results of this were not proven in some previous works, while nonlinearity was justified.

Most nonlinear links concerning social factors have U-shape or inverted U-shape, where the direction of effect on one factor is reflected on another. It can be negative in a way that points to minimum value or positive that points to a maximum value, respectively in the same curve, while S-shape is common in relationships concerning socio-economic factors (Rondan-Cataluña et al., 2015). The theory behind the U-shape is that the relationship between the independent and dependent variable starts at a decreasing rate or at an increasing rate until it reaches the "turning point" (Haans et al., 2016). It is considered the maximum in the case of an inverted U-shape, or the minimum in case of U-shape, but in S-shape, there are two "turning points." Herein lies the danger of the linear assumption, which may cause bias in the interpretation as well as inconsistent estimates; and this is what we seek to avoid in proving non-linearity.

In the light of that, this study may contribute to conceptualizing the theory of technology acceptance such as learning delivered via the web, by expanding the perception of the basic structures in a TAM model. It is extended by the factors of HCI to include non-linear relationships of quadratic, cubic, logarithmic, S-curve and other potential models that contribute to developing a more comprehensive insight into explaining the complex nature of user perceptions and motivations as proven by Salam et al. (2021), and underlie the importance of new results in comparison with linearity.

2.2 HCI Factors (Interface and Interactivity)

Human-computer interaction (HCI), which is concerned with the interaction between users and computers, was adopted as a term in the 1980s (Preece et al., 1994). The two terms illustrate HCI: first, the interface, which is described as a visible piece of any digital system the users can touch, hear or see (Head, 1999); second, interaction, which concerns the users' activities such as typing through the keyboard. E-technology designers are working actively to enhance the users' interaction with e-learning through creating user-friendly devices, interfaces, systems, tools, and applications. But they do not reach effective designs because of their misunderstanding of the issues related to HCI (McCracken and Wolfe, 2004). For example, it should be a reciprocal dynamic between the users regarding what they perceived about the visual organization of the interface and the designers regarding their perspective as the information organizer on the site. Users may access the information on the web for different purposes, which can be highlighted in terms of some aspects of HCI issues that may not be considered by the designer. In general, the engineers apply HCI concepts to good website design, but they do not know effective ways to achieve a user-friendly design.

To increase and maintain the users' response, systems should be designed carefully at the design stage. That's done by developing techniques and tools that ensure adaptation to the users' activities; deriving psychological, social, and organizational factors linked with effective usage of technology; and achieving efficient, safe, and effective interaction (Preece et al., 1993). And all that requires a wide range of skills such as understanding the users, estimating the software engineering capabilities, and applying appropriate graphical interfaces. HCI, as a science, can be classified as anthropology and sociology, whereas interactions play a major role among technology, organization, and work; as for psychology, the user behaviour is analyzed by applying the empirical analysis, and in computer science, too (Hewett et al., 1992).

Shiau et al. (2016) outlined the main trends in the intellectual core of HCI, which were derived from 75 highly cited articles out of 1168 and classified under 12 clusters. User interface design and its effect on technology acceptance, the task of the HCI system such as user navigation behaviour, and user acceptance of technology are shown in Figure 2.1.

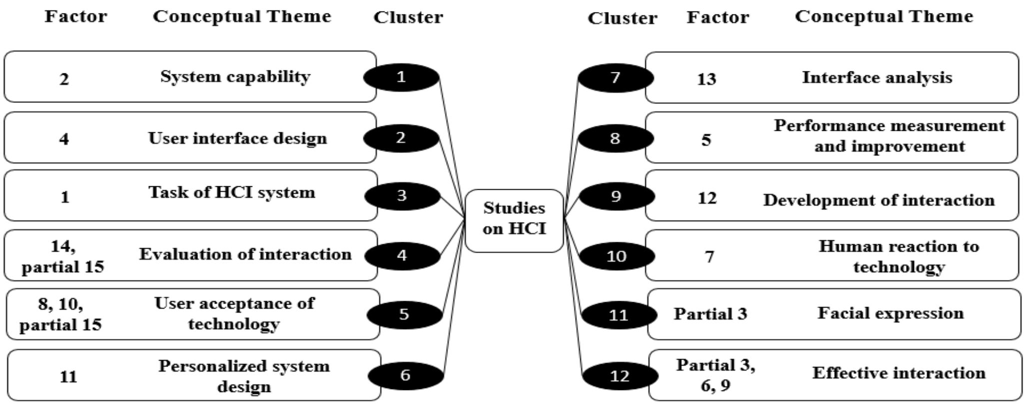

Figure 2.1 Studies on HCI (source: Shiau et al., 2016)

2.3 The Models of Technology Acceptance

Several models were developed to enhance the users' perception of new technologies such as TRA, TAM, TPB, TAM2, TAM3, UTAUT, and DeLone and McLean Information Systems Success Model. All these models are the most commonly used ones in e-technology acceptance.

To keep pace with the rapid technological developments, and the need to promote the adoption of any new web-based technology , including e-learning and web-based learning, researchers developed several models such as DeLone and McLean information systems success model (DeLone and McLean, 2003), TRA, TAM, TAM2, TAM3 TPB, UTAUT, and UTAUT2, which were the most often used ones.

TRA (Theory of Reasoned Action) was developed by Fishbein and Ajzen (1975) by drawing the distinction between attitudes constructs, where behavioural intention as a predictor to the performance of the user is jointly determined a by subjective norm and attitude. TAM (Technology Acceptance Model) was developed by Davis et al. (1989), to explain why users accept or reject an innovative IS. TAM2 was developed by Venkatesh and Davis (2000), by extending TAM with cognitive instrumental variables (output quality, job relevance, and result demonstrability), and social influence variables (voluntariness, subjective norm, and image), which were ignored in TAM. TAM3 is the development of TAM2 where the determinants of perceived "ease of use" are explained by anchor beliefs about computer use (computer self-efficacy, perception of external control, computer playfulness, and computer anxiety) and hands-on experience (perceived enjoyment, and objective usability) (Al-Sayyed & Abdalhaq, 2016). TPB (Theory of Planned Behavior) is an extension of TRA, which was developed to mitigate the original model's limitations of behaviours over which people are not fully voluntarily controlled (Ajzem, 1991). In addition, UTAUT (Unified Theory of Acceptance and Utilization of Technology) was formulated by Venkatesh et al. (2003), and was compiled from eight models and theories (TRA, TAM, MM, TPB, C-TAM-TPB, MPCU, IDT, and SCT) to explain intentions and subsequent use behaviour regarding IS usage by four main predictors groups (performance expectancy, social influence, effort expectancy, and facilitating conditions), which were integrated with behavioural intention (Venkatesh et al., 2003).

2.3.1 Technology Acceptance Model (TAM)

TAM was developed by Davis (1989) as an adaptation of the Theory of Reasoned Action (TRA) that was developed by Fishbein and Ajzen (1975) to find its origins in the field of social psychology. And it has become one of the most influential research models in the subjects of information systems (IS) and information technology (IT) acceptance, and widely applied its main determinants, including perceived ease of use and perceived usefulness, to predict individuals' intention to use new technologies (Figure 2.2). Furthermore, over the past decade, TAM has received considerable attention from researchers who learned its critical role in designing different online users' interfaces as their needs (Chen et al., 2011).

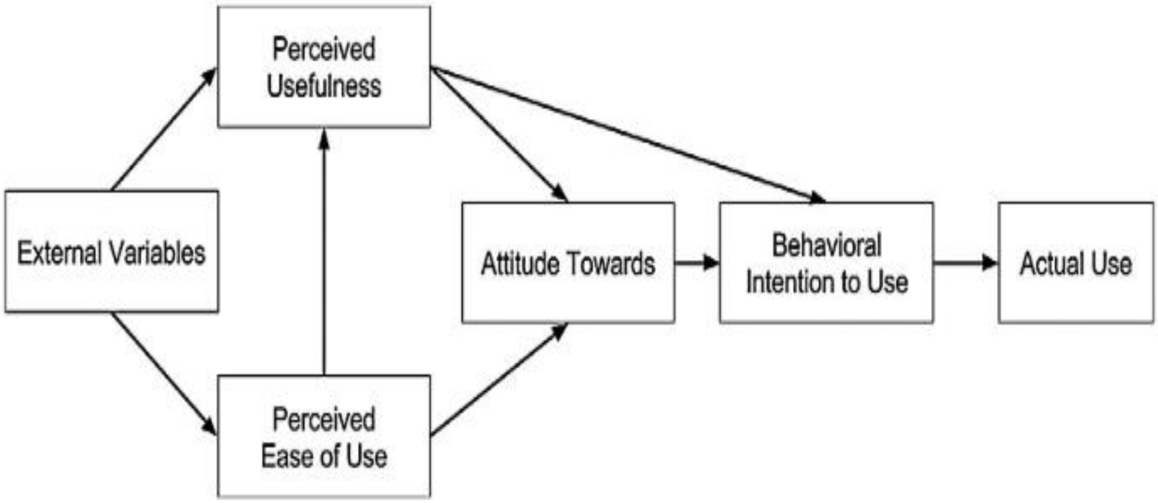

Figure 2.2 TAM Model of Chen et al. (2011)

Understanding the aspects related to the mechanisms that help adopt and use technology is essential in achieving human-computer interaction, and perhaps one of the most common models that deals with these mechanisms is the technology acceptance model TAM (Hornbæk & Hertzum, 2017).

However, the TAM model has some limitations. Firstly, this model demonstrates around 40% of technology acceptance in terms of explanatory power. Secondly, the correlations between its dependent and independent factors are inconsistent in different settings and contexts (Al-Aulamie, 2013; Hakami, 2018). As an instance, the impact of factors linked with perceived EoU has been proven as significant in several studies whereas insignificant in others. Thirdly, it uses behavioural intention more (such as interpersonal influence) than behavioural expectations (in which the use of IT is investigated) to predict the intentions of employees about the use of technology (Ajibade, 2018).

In addition, the correlations among the TAM constructs have been proven and confirmed in many studies while its relative strength of the influences varies with the context, which forced researchers to identify moderators to capture aspects of the context important in the case of technology acceptance (Hornbæk & Hertzum, 2017).

2.3.2 DeLone and McLean Information Systems Success Model

DeLone and McLean (1992) developed an information system success model consisting of six factors related to system success: user satisfaction, use, system quality, information quality, individual impact, and organizational impact (DeLone and McLean, 1992). This pioneering model established the basis for evaluation of the success of information systems on the assumption that the actual use of any closed system was related to user satisfaction (Figure 2.3).

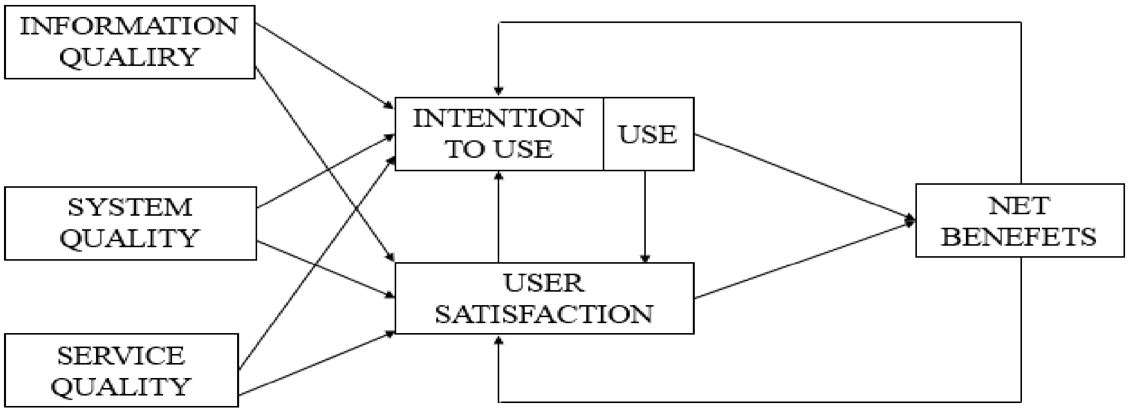

Figure 2.3 DeLone and McLean information system success model (2003), (DeLone and McLean, 2003)

2.3.3 Theory of Acceptance and Use of Technology (UTAUT)

Theory of Acceptance and Use of Technology (UTAUT) which was formulated by Venkatesh et al. (2003), has been used by many researchers as a fundamental theory focusing on users' behaviours toward information technology and explaining their intentions to accept technology as e-learning (Figure 2.4). This model is compiled from eight models and theories, which are: theory of reasoned action (TRA), technical adaptation model (TAM), motivational model (MM), theory of planned behaviour (TPB), a model of combining TAM and TPB (C–TAM–TPB), a model of PC utilization

(MPCU), innovation diffusion theory (IDT), and social cognitive theory (SCT) (Lin, 2019). The constructs of this theory are grouped in (performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioural intention) (Tan, 2013).

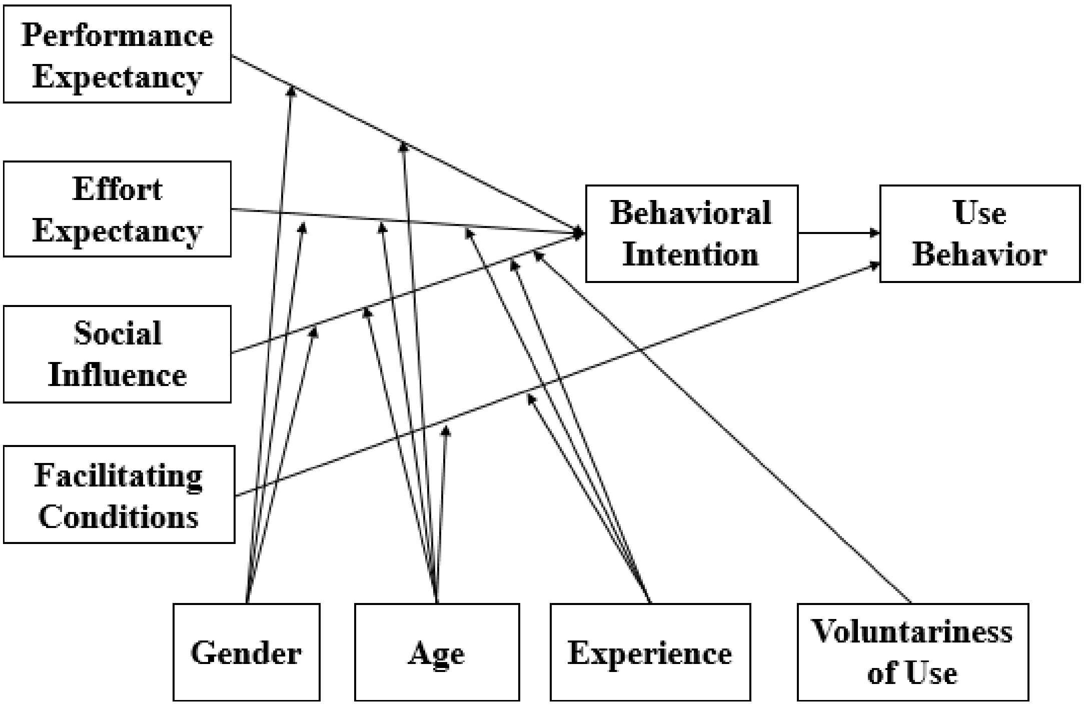

Figure 2.4 Theory of Acceptance and Use of Technology (UTAUT), (Venkatesh et al., 2003)

2.4 Student Success (SS)

The use of dynamic information and communication technology (ICT) at present is one of the things that revitalize the educational process as the students' tendency to use digital technology is higher than their desire to receive educational and training courses and lessons in the traditional way. Nevertheless, these capabilities that facilitate collecting data, converting them into information, and then exporting them into processed data do not provide in detail a description of the extent of their impact on students success, according to all the studies that have been interested in this field (Martins et al., 2019).

According to Astin (1984), a students' success can be measured by the extent to which an individual interacts with an institution and vice versa (Astin, 1984). Furthermore, to measure student success, van Rooij et al. (2018) used three indicators. One of them was related to grade point average (GPA). It was done calculating students' average grades of the courses they had taken in the first period of the study year. The second measure is related to students' intention to going on the three-year university bachelor's program (van Rooij et al., 2018).

2.4.1 Studies conducted on student success

van Rooij et al. (2018) investigated the effects of behavioral and psychological factors, such as academic self-efficacy, intrinsic motivation, degree program satisfaction, and self-regulation on student success based on three indicators: intention to persist, GPA (grade point average), and ECTS (attained number of credits). The presented conceptual model in this empirical study shows that 243 students' outcomes from the Netherlands University were influenced directly by an academic adjustment. And thus, with this adjustment, the students had a higher GPA and had more successful interactions in the academic experience (van Rooij et al., 2018).

Martins et al. (2019) present a conceptual success model that ensured, through a questionnaire, a net benefit obtained by 450 students from higher education in three different Portuguese universities with education management information systems (EMIS). The study findings denoted that students' satisfaction and engagement in continuous EMIS usage are the main predictors of net benefits. These predictors strongly correlated with two determinants: information quality and service quality (Martins et al., 2019).

In order to prove online learning and teaching tool effectiveness and their impact on student success, González et al. (2010) randomly assigned 121 students from an introductory course to different groups and guided them in using online tools. The results clearly show that students' practical exam results showed improvement in their grades by about 5% related to online questions and materials (González et al., 2010).

Ifinedo et al. (2018) surveyed 126 undergraduate students from a Canadian university through a cross-sectional questionnaire to provide empirical information on factors affecting the users' outcomes in Moodle in a blended learning context. The external supports were not correlated with users' outcome enhancement. So, they recommended conducting more studies in this aspect (Ifinedo et al., 2018).

2.5 The subject of e-learning for online education purposes

The term e-learning as an e-technology tool is an abbreviation for electronic learning, which needs software, hardware, complex technical support, and communication infrastructure, as well as several electronic activities such as e-commerce, e-learning, e-invoicing, e-marketing, e-procurement, and many others. Consequently, a variety of e-technologies are implemented and developed in enterprises (Malo, 2012).

Koh and Maquire (2009) describe e-technology as various forms of IS, IT, IT/IS, and ICT used with the network architecture support of the Internet, Extranet and/or Intranet to assist personal, organizational, institutional, and business activities.

Many universities use e-learning management systems as a platform that aims to conduct online courses such as Moodle, which is well known among instructors in different countries due to its economy and easiness (Nicholas-Omoregbe et al., 2017).

In Turkey, Kadir Has University hosted a Moodle infrastructure customized to serve in web-based teaching and used as an asynchronous application called "KHAS Learn system." The Moodle application enables sharing course content; it is equipped with tools that support online self-assessments such as quizzes and assignments; it includes discussion boards and forums; it offers online training for faculty members; it provides informative and supportive activities addressing students; and it enables conducting 18 types of exam questions, which can be adapted in accordance with the courses (Khairuzzaman, 2020).

2.5.1 Studies conducted on e-learning and e-learning acceptance

Šumak et al. (2011) combined 42 independent studies from different databases (IEEExplore, ScienceDirect, ACM, etc.), which were analyzed based on a combination of keywords, either related to e-learning technologies (eLearning, e-Learning, web learning, online learning, etc.) or keywords related to technology acceptance theories. The results from reviewing literature indicated that TAM is the most used theory in e-learning acceptance studies as a ground theory, followed by UTAUT; and students are the most common user type in existing research. The researchers asserted that the perceived usefulness and the perceived ease of use tend to be the main factors that can influence the attitudes of users toward the actual use of e-learning technology (Šumak et al., 2011).

Abdullah and Ward (2016) analyzed the 20 recent studies presented at conferences, and 87 papers published in the last 10 years, which related to extended TAM, to investigate the acceptance of e-Learning. They chose from a range of journal databases such as (IEEExplore, Taylor & Francis Online, ScienceDirect, etc). The researcher conducts a quantitative meta-analysis to identify the most commonly used external factors in the context of e-learning acceptance. The results show that self-efficacy, enjoyment, subjective norm, experience, and computer anxiety are the most used ones in testing their effects on perceived usefulness and perceived ease of use (Abdullah & Ward, 2016).

Cidral et al. (2018) pointed out the timeline of e-learning studies in different milestones as shown in Figure 2.5, which accordingly focused on customization and course contents from 2001 to 2003. Then, they were concerned with the e-learning platforms’ usability and the continuity usage from 2004 to 2006. Later, they focused on e-learning methodologies and users' satisfaction level from 2007 to 2009. From 2010 to 2012, satisfaction and e-learners’ expectations were taken into consideration more. The earlier studies highlight the effect of users' characteristics on e-learning success from 2013 to 2016, besides the latest research that focused on the role of interaction and users' attitudes in the success of e-learning systems (Cidral et al., 2018).

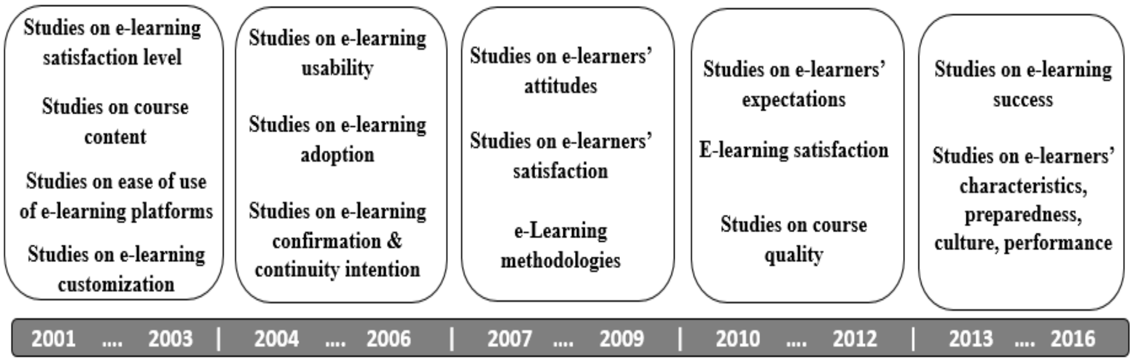

Figure 2.5 E-learning studies timeline, source (Cidral et al., 2018)

2.5.2 Studies conducted on HCI and e-learning

Cho et al. (2009) developed a theoretical model that underlined the importance of perceived user-interface design, which included perceived functionality and system support, for intention to use e-learning. The researcher adopted the survey approach distributed to 100 randomly selected university students from seven universities in Hong Kong (Cho et al., 2009).

El Said (2018) employed a qualitative study by conducting semi-structured interviews with 52 university undergraduates in a developing country, to present the factors that enhance students' willingness to use the mobile student portal, which is used as a platform for interactive services. Some of these factors were introduced newly in the adoption of mobile users' portals, in the context of mobile human-computer interaction (El Said, 2018).

Cahyono and Susanto (2019) explained the TAM development with five factors that affect the main acceptance factors: perceived ease of use, relative advantage, and cognitive variables. These factors are attitude, affective, psychomotor, perceived mobility, and relative advantages. Also, the factors were moderated by visual design components, perceived usefulness, perceived mobility, and perceived interactivity. The researcher measures the value of psychomotor by assuming eye movements and measure the cognitive value by assuming brain waves, while affective was tested based on the results of 48 questionnaire respondents in Indonesia (Cahyono & Susanto, 2019).

2.5.3 Studies conducted on COVID-19 and e-learning

Baticulon et al. (2021) identified the e-learning barriers in a developing country, which they classified under five categories: technological, institutional, domestic, individual, and community barriers. The researcher sent an electronic questionnaire based on a multiple-choice Likert scale and open-ended questions to obtain data which provided suggestions under the COVID-19 restrictions. Nonparametric tests showed that 41% of the students were mentally and physically capable of engaging in online-based learning (Baticulon et al., 2021).

Subedi et al. (2020) conducted a descriptive cross-sectional online questionnaire to assess the impact of web-based learning among teachers and nursing students who were selected from thirteen different nursing colleges of Nepal during the COVID-19 pandemic. This study indicated a significant correlation between attitudes and activity statements with the respondents' selected demographic variables. Thus, the researcher concluded that to overcome the real issues faced by students while running online courses is to make the e-learning system more efficient (Subedi et al., 2020).

3. STUDENTS' WEB-BASED ACTIVITIES AS A MODERATOR

The purpose of this part in this this study is to investigate if students' activities on systems web-based moderate the effect of human-computer interaction (HCI) factors on ease of use and usefulness of e-learning and their success (SS) at the time of the COVID-19 pandemic. To answer the questions that addressed the relationship between HCI, e-learning acceptance, and SS, the researcher surveyed 103 students from Kadir Has University whose grade and activity logs were accessible. The survey was related to their perceived course webpage design, system and content quality, interactivity, usability and functionality, and self-assessment. The results show that most of the hypotheses of this study have been proven, a comprehensive conceptual model was developed, and the student grades in the online courses improved their GPA. The findings further reveal that students' activities moderate the effects of course environment and content quality on perceived usefulness and the effect of the course evaluation' system on perceived ease of use, where the changes in R^2 ranged between 0.041–0.074. That means including logs as a moderator would increase the explanatory power of the effect of HCI factors on e-learning acceptance which together explained 54.9% of the variance in perceived success (SS), where U is the strongest determinant of SS.

3.1 General Problem Statement and the First Part Objectives

The spread of the COVID-19 pandemic has changed the learning and teaching methodologies and methods worldwide, especially under the technology advancement. To maintain the continuity of education and activate the role of the parties in the educational process at the lowest costs, many governments and educational institutions have resorted to adopting e-learning as the most effective and safest method from their point of view.

Most of the previous studies that focused on accepting technology examined the influence of external factors related to behaviours and intentions, but few of them focused on the user perceptions toward the web-based features in terms of users' experiences through interacting with the computer and the effect of these constructs on technology adoption.

In addition, according to our research, there are no studies that focused on the impact of technology acceptance on students’ perceived success, after the actual use of e-learning in the presence of conditions that compel them to do so, including the COVID-19 pandemic. Moreover, most studies focused on the effect of gender and age as a moderator of the relationships that link constructs in technology acceptance models such as the TAM model. In this study, we need to test an aspect related to students' activities, during their use of the system, and the extent of its effect as a moderator.

Understanding the core knowledge in the HCI fields, e-technology acceptance, and user behavior which have become a growing trend recently, it is necessary to study the effects of related factors on students’ success in the time of COVID-19 outbreak. So, this study aims to:

- Determine the factors that are associated with human-computer interaction fields which affect students’ e-learning acceptance and success.
- Find correlations between those factors which determine the strength of negative or positive influence on the acceptance of e-learning and students’ success.
- Determine which of these factors have the most significant impact on the adoption of e-learning.
- Investigate if users’ activities during the online learning process moderate the relationship between HCI, e-learning acceptance, and students’ success.
- Create a comprehensive model that explains why students in Turkish universities accept e-learning and thus success.

To answer these questions, this study first adopted a semi-structured questionnaire based on previous studies and expert opinions. We obtained user results regarding the main HCI constructs that may affect e-learning acceptance with respect to TAM and their perceived success. Second, the results were coded using grounded theory (GT). To validate the coded results we assessed the homogeneity of the obtained data and categories that rely on exploratory factor analysis and Cronbach's alpha. Additionally, a conceptual model of factors affecting students' perceptions was constructed in terms of technology acceptance. Third, the structured survey was designed to collect sample data; and an empirical analysis was conducted to validate the theoretical model using linear and multilinear regression analysis via SPSS-v25 software. Fourth, the students' web-based activities were collected from the system logs related to the respondents. Then we investigated its moderating effects on the hypothesized causal relationships through the macro PROCESS for SPSS. Finally, the proposed model constructs were discussed, and some recommendations were put forward to improve the interactivity and interaction between humans and computers, e-learning acceptance, and perceived success from technical and perception aspects, based on students' experiences.

3.2 Research Model and Hypotheses Development

The objective of this study was to identify the main HCI factors effective on technology acceptance and student success at Kadir Has University and investigate the influencing of student activities as a moderator of the links between constructs in terms of users' experiences. Given the subject of the study and the sampled data, the grounded theory was used to construct a theoretical model of the main factors affecting users as one of the most efficient options in qualitative research (Sargolzaei et al., 2021). Grounded theory is a flexible and systematic approach that aims to collect and analyze qualitative data to construct theories grounded in the data (Holt et al., 2022). For this part of the study, the literature was reviewed and upon which a semi-structured questionnaire was designed and used for interviewing twenty experts and students in the university. Qualitative ground theory studies should generally include twenty to thirty interviews (Hvannberg et al., 2019).

In the second step of this part of the study, data was coded based on Strauss and Corbin's (2015) technique, whereas open coding, axial coding, and selective coding were implemented. In open coding, we obtained a number of words and phrases from data related to user experience with their perception indicators linked to interface design and interactivity. Then, we closely examined the data, broke it down into properties, made comparisons, and re-questioned it to reach saturated concepts. In axial coding, we identified a final set of categories and relationships. From concepts to categories, a set of ten subcategories also emerged from these dimensions: perceived course webpage design, perceived quality, perceived interactivity, perceived usability, perceived functionality (Figure 3.1), perceived ease of use, perceived usefulness, self-efficacy, perceived success, and the users' activities through the system (Figure 3.2). The axial coding process was advanced during the previous process through analysing data, clustering concepts, and identifying the relationships among them. In selective coding, we obtained the core categories which moved toward a generation of theories that represent the main phenomena of this study. Consequently, this helped with hypothesising and generalising the relations among abstractions and their properties, such as the relationship between human-computer interaction factors, technology acceptance factors, self-assessment factor, and students' success factor. Further, the effect of logs which represent the students' activities was added as a moderator to these relations.

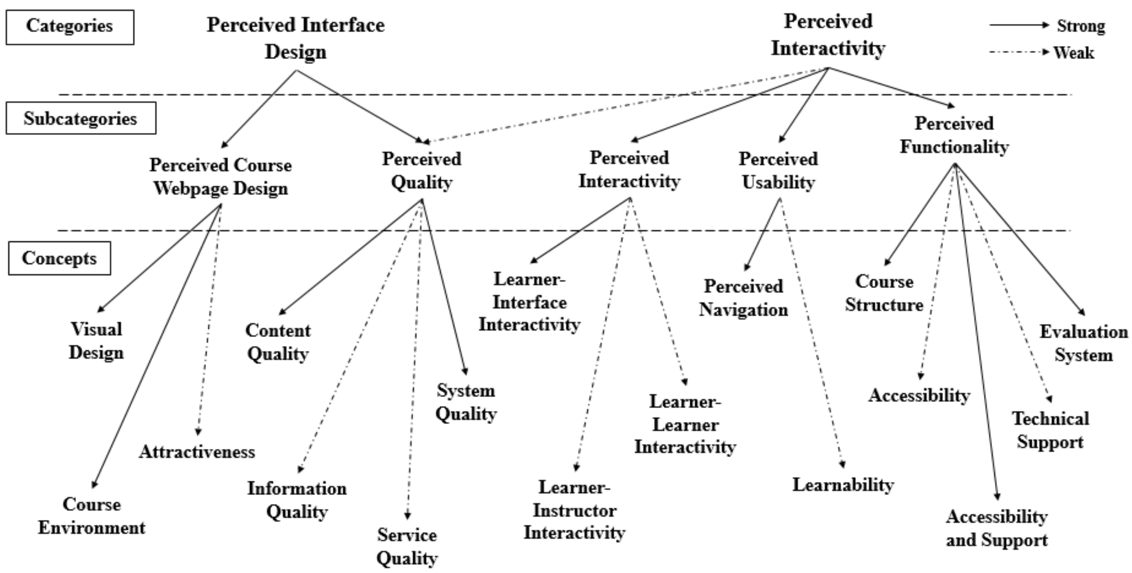

Figure 3.1 Categories and concepts that emerged during the ground theory process

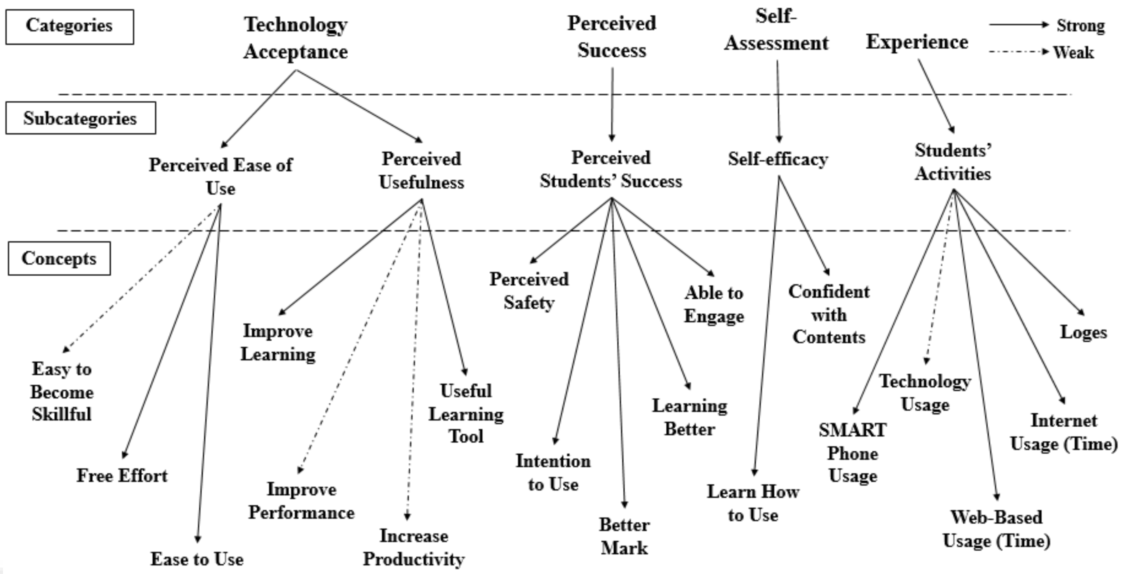

Figure 3.2 Categories and concepts that emerged during the ground theory process

3.2.1 Perceived ease of use, and perceived usefulness

Perceived ease of use (EoU) is the main factor proven in TAM, which is defined as the extent to which users believe that any technology usage needs free effort (Davis et al., 1989; Al-emran, 2021). Furthermore, EoU is strongly linked with the growth of users' experiences in using specific systems, thus change or form their convictions over time toward the actual use (Venkatesh, 2000). Appraisal of ease of use is a vital step in the development process and overall software design (Al-tahat, 2021).

Perceived usefulness (U) is another crucial factor that has been proved in TAM, which strongly affects users' acceptance of any system-based new technology. In this context, PU is defined as the strength of users who believe that using the system will improve their work performance (Venkatesh and Davis, 2000; Garcia, 2017).

Perceived ease of use and perceived usefulness positively affect the attitudes toward an information system. Furthermore, they positively affect the individuals' intentions to use, and the acceptance of the information system. Besides, perceived ease of use positively affects the perceived usefulness, and both perceived ease of use and perceived usefulness are influenced by external variables (Chen et al., 2011).

TAM “has been applied in various information technology and information system areas" (Chen et al., 2011). And several studies employed several measures to prove the main factors of engagement in TAM (Venkatesh, 2000; Venkatesh and Davis, 2000; AL-Ammari and Hamad, 2008; Venkatesh and Bala, 2008; Phua et al., 2012), and have found that behaviour intention (BI) has a close correlation with U and EoU. However, no studies tested the association of these factors with student success. Hence, the researcher developed hypotheses as follows:

Hypothesis 1: Perceived usefulness will have a significant positive effect on the student success in Kadir Has University.

Hypothesis 2: Perceived ease of use will have a significant positive effect on the student success in Kadir Has University.

Hypothesis 3: Perceived ease of use will have a significant positive effect on usefulness of e-learning.

3.2.2 Self-efficacy

Self-efficacy (SE) refers to self-assessment (Tran, 2016) of an individual ability to apply computer skills to complete particular tasks, and measures users' estimation of their ability to use computer technologies to complete particular tasks. This factor has been estimated as the most widely accepted determinant of perceived ease of use. So, students are more likely to use the e-learning systems, if perceptions toward their ability to use the systems provided by their universities are high (Binyamin et al., 2018).

Abdullah and Ward (2016) analyzed 107 studies related to the extended TAM. Some were chosen from conferences, and most came from a range of journal databases such as IEEExplore, Taylor & Francis Online, and ScienceDirect, published in the last 10 years. It was proven that SE has a weak significant positive relationship with the perceived usefulness of e-learning, where the overall average path coefficient is Beta=0.088 in 63% of these studies of interest. Also, it has a significant positive relationship with perceived ease of use of e-learning, where the overall average path coefficient is Beta=0.342 in 80% of these studies of interest (Abdullah & Ward, 2016).

The researcher assumes that users with high SE are more likely to accept e-learning, with the presence of HCI factors effects, and their success. So, the researcher developed hypotheses as follows:

Hypothesis 4: Self-efficacy will have a weak significant positive effect on the usefulness of e-learning.

Hypothesis 5: Self-efficacy will have a significant positive effect on perceived ease of use in e-learning.

3.2.3 HCI main factors

The process of developing human-computer interaction is highly related to two aspects: "Interface" and "Interactivity." So, to maximize the user response by developing "student-friendly" web-based sites (Issa & Isaias, 2015), we have to take into account the users' perceived interface design factors and perceived interactivity factors. "A proper interface design should satisfy the users´ needs, capabilities and limitations" (Ruiz et al., 2020).

3.2.3.1 Perceived interface design

The heterogeneity of web-based platforms and learners' expectations, for example, in terms of ease of use, has turned the user interface design into one of the most influential elements to consider when enhancing related applications since it connects end users with software functionality (Ruiz et al., 2020). A good interface design may help the user to accomplish many tasks and operate specific functions within web-based systems in terms of HCI. In this study, we are concerned with two main variables, categorized as perceived course webpage design, which is a visual design, and a course environment.

Visual design (VD) was stated as a significant effect of visual design components such as colour, layout, typography, and media on the users' performance in using the websites (Cahyono & Susanto, 2019). The interface shapes may cause different psychological reactions from learners (Wang et al., 2021).

Course environment (CE) will be designed and built to support using the available servers, instructional materials and will target the specific needs of the students. Whereas, the course design plays a vital role in how learners or users interact with the system. In some cases, the learners are not familiar with the available features, which include graphics for navigational or for making them appear pleasing rather than for instructional or educational purposes, so designers have failed to implement or create an engaging learning environment that a lines learning expectations (Conley et al., 2020). The computer communications' technical development leads to enhancing user interface applications and tools, which are compatible with web-based tools, and linking them with an underlying database. Thus, a new type of system appeared called course environment that supports the users (Veglis and Barbargires, 2001).

Content quality (CQ) represents the sufficiency of materials (Binyamin et al., 2020), and various types and manifold formats of information (Tran, 2016). When it is high, it influences students' satisfaction and intention to use systems such as e-learning (Salloum et al, 2019).

System quality (SQ) is clarified by Gable et al. (2008). From design and technical perspectives, it is a measure or users' evaluation of an information system, defined by Oun-Alla (2013) as "a term to describe the quality of the content of information system." Additionally, an efficient e-learning system depends on system quality (Oun-Alla, 2013). The adoption of the systems linked with education-based IT and IS was highly correlated with the functional and technical quality of these systems (Navimipour & Zareie, 2015). DeLone and McLean (2004) concluded that SQ is a critical success factor for users' satisfaction and their intention to use the new system according to the IS success model.

In general, the clear variables of perceived web-based system quality are flexibility, access convenience, ease of use, integration, response time, sophistication, reliability, accessibility, stability, system speed and usability, navigation, and network speed (Lee et al., 2009).

To examine the importance of enhancing the users' perceived interface in achieving their acceptance of e-learning and success, the researcher developed hypotheses as follows:

Hypothesis 6: VD, CE, CQ, and SQ will have a significant positive effect on the student's perceived U of e-learning.

Hypothesis 7: VD, CE, CQ, and SQ will have a significant positive effect on student's perceived EoU e-learning.

3.2.3.2 Perceived interactivity

Interactivity in an online educational context refers to the activity between learners and computers in the context of HCI, (Issa & Isaias, 2015).

Learner-interface interactivity (LInt) is related to web menu design, including maps, icons, control bars, screen design, etc. When developing the design to make it user-friendly, it increases the interactivity and enhances technology acceptance (Eraslan Yalcin & Kutlu, 2019). Liu et al. (2010) affirm that the clear text and suitable visual items in teaching materials could affect students' perceptions and usage preferences (Liu et al., 2010). Therefore, they easily find the right way to learn (Mouakket & Bettayeb, 2015).

Navigation (Nav) behaviour constitutes a trend included in the task of the HCI system, which was clustered and identified as one of twelve intellectual core groups of HCI (Shiau et al., 2016). The creation of effective websites requires various methodologies addressed by details such as navigation, graphics, multimedia, and typography (Issa & Isaias, 2015). Therefore, navigation is the main factor approaching the usability embedded in HCI, where poor usability of web-based system navigation severely reduces or limits the learning or teaching effectiveness (Jin et al., 2022).

The researchers debate that the conformity between users' cognitive, sensory, and motor capabilities and design attributions contributes to HCI. Nevertheless, the previous studies could not introduce a deep understanding of how specific user characteristics, such as technical experience, education, and cognitive capabilities can influence their navigation behavior (Li & Luximon, 2019).

Accessibility and technical support (AcS) is related to technological tools, features, and instructions used to facilitate the interactivity with instructors and other learners via email chat, group centres and other tools for communication; and it is used to support web-based courses that may affect the frequency with which students interact with needed materials, receive adequate feedback, and social presence, although their learning success was not evaluated (Rubin et al., 2013).

Course evaluation system (CES) is important as pass rates and exam results conducted through self-assessment affect the overall success indicators of Higher Education Institutions, and thus students' success in this type of educational process based on ICT improvement (Ćukušić et al., 2014).

Course structure and content (CSC) is another factor which refers to the perceived ability of the flexibility of the e-learning system in accessing assessment media and instructional materials, according to Tran (2016). It provides access to the course content, complete quizzes, online tests, and return homework. The overall accessibility and support, course evaluation system, and course structure and content reinforce the system functionality.

To investigate the effects of increasing the perceived interactivity of students on improving the acceptance of online learning and thus the success of students, the researcher developed hypotheses as follows:

Hypothesis 8: LInt, Nav, AcS, CES, and CSC will have a significant positive effect on the students' perceived U of e-learning.

Hypothesis 9: LInt, Nav, AcS, CES, and CSC will have a significant positive effect on students' perceived EoU e-learning.

3.3 Mediating and Moderating Effects

Although a lot of previous studies focused on testing the interrelationships between perceived usefulness (U), perceived ease of use (EoU), and users' behavioural intentions; or between these factors and the extension factors of the TAM model, there is still a scarcity of research that tests the demographic and descriptive statistics such as age and GPA, or the experience such as technology usage, like potential moderators (Kim et al., 2019). Binyamin et al. (2020) mentioned that several studies adopted gender as a moderator variable when applying technology-acceptance models, such as UTAUT and

UTAUT2. Furthermore, there is a scarcity of studies that test the effect of interactive activities as a moderator of the interaction between humans and computers, as well as their perceptions toward the acceptance of new technology, and their achievement.

Considering the existing TAM studies in the literature, mediation influences can be found. The user’s attitudes and perceived usefulness mediate the relationships between perceived ease of use and smart service belief factors and behaviour intention to purchase (Gao & Huang, 2019).

In the light of demographic characteristics, technology usage, or activities during the learning process, moderator variables and the mediator factor would increase the explanatory power of the TAM main factors, so the researcher developed hypotheses as follows:

Hypothesis 10: Perceived U will mediate the positive effect of EoU on SS in using e-learning.

Hypothesis 11: Personal information (gender, age, GPA, academic year, and course name) moderates the positive effect of perceived interface design factors (VD, CE, CQ, SQ, LInt, Nav, AcS, CES, and CSC) on the student's perceived U or EoU of e-learning.

Hypothesis 12: Technology usage (devices used, tools used, times, and internet usage) moderates the positive effect of perceived interactivity factors (VD, CE, CQ, SQ, LInt, Nav, AcS, CES, and CSC) on the student's perceived U or EoU of e-learning.

Hypothesis 13: Users’ online activities during learning process (logs) moderates the positive effect of perceived interactivity factors (VD, CE, CQ, SQ, LInt, Nav, AcS, CES, and CSC) on the student's perceived U or EoU of e-learning.

Based on grounded theory outcomes and reviewing previous research, the researcher proposed a conceptual model presented in Figure 3.3. This model shows HCI factors integrated with TAM's main factors, which have been proven by many researchers and experts as valid to predict users' intention toward e-learning’s actual use. In this proposed model, the researcher wants to prove the effectiveness of these factors on the student success to be engaged in online courses and achieve many of the desired results.

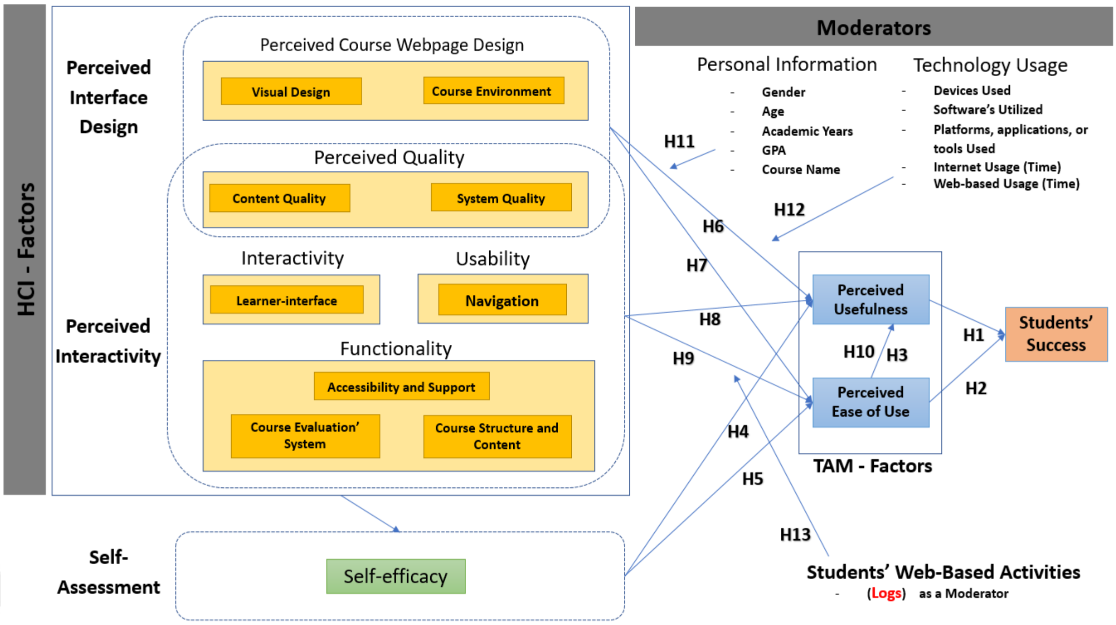

Figure 3.3 The researcher's proposed conceptual model (e-LASS)

3.4 Methodology

In this part of this study, the two approaches are integrated during data collection and analysis, with the qualitative method first in sequence to support iterative data collection and analysis in a context of theoretical sampling and the quantitative method prioritised in implementing the conceptual model to achieve the main research objectives. So, this research was divided into two parts. First, there is the qualitative part where the data collection was held through two different methods, literature review, and afterwards, a semi-structured questionnaire as the main tool to collect qualitative data for the grounded theory analysis. Consequently, the data collected in the first part contributed to the identification of the tested constructs in the proposed conceptual model. Second, there is the quantitative part where a survey was prepared and conducted to provide measures for factors included in the proposed model. These measures were developed via exploratory factors analysis. Finally, a conceptual model was developed using linear and multi-linear regression analyses.

3.4.1 Literature review:

A literature review was mainly designed to review existing literature and publications on the concept of Human-Computer Interaction (HCI), e-learning and its applications, e-learning benefits, challenges and its efficiency, technology acceptance models, the status of e-learning in Turkey, and grounded theory background. Recent significant studies and reports are reviewed related to critical factors influencing e-learning adoption in several fields by many users in different countries, particularly in Turkey.

3.4.2 Data collection:

Data collection includes two steps: first, there is acquisition of a semi-structured questionnaire upon reviewed literature data for the model construction in qualitative analysis based on the GT; and second, there is acquisition of a structured survey data for empirical analysis in a quantitative method based on the regression analysis. In the light of the requirement to have the respondents at a certain cultural level, and cognitive ability according to grounded theory methodology, samples were taken purposefully until saturation occurred, where twenty experts and students from Kadir Has University were interviewed, using a semi-structured questionnaire outline. It was launched around the study goal and mainly set oriented questions to fully understand the respondents' perception in terms of human-computer interaction and technology acceptance, given their experiences and activities via web-based tools.

Furthermore, in this study, the researcher obtained the authority to monitor the anonymous students' interactive activities on the system (a suitable representative sample of students in Kadir Has University as a case study). In addition to tracking the development of their grades in the online courses, their registration numbers were relied on. Moreover, the researcher approached survey-based research, which includes several items related to all these study variables and factors, as follows: we designed the survey through a questionnaire; the first draft of the questionnaire statements was dependent on specific previous empirical studies and the viewpoint of experts; we reviewed the English version of the questionnaire, and adjustments were made; after that, we ensured the questionnaire's validity and reliability; then, we distributed this survey. This fit with the quantitative approach.

3.4.3 Data analysis:

The researcher processed the data analysis using proper software called Statistical Package for the Social Science (SPSS-v25), which is useful for analyzing survey data and getting the causal relationships between questionnaire elements. SPSS fits the quantitative approach. The personal information, as well as different responses were analyzed based on the percentage of the frequency of participants; statistical differences among survey participants were outlined, and explained by conducting a t-test; then, ANOVA tests were used to test correlations between qualitative and quantitative factors. Furthermore, linear, and multilinear regression analyses were used to test the research hypotheses and determine which ones would be supported. As for moderation and mediation, the researcher used the macro-PROCESS for SPSS.

3.5 First Survey and its Quality

A structured survey has been used to test the researcher's hypotheses. Quantitative variables were related to the SS factor integrated with TAM main factors (Table 3.1), self-assessment factor (Table 3.2), and HCI factors which include perceived interface design (Table 3.3) and perceived interactivity factors (The data required in this research need an appropriate tool, as well as a survey technique to collect respondents' perceptions based on the Five-Likert Scale about the interface and interactivity of the web-based teaching. It is also necessary to examine the correlation of these factors with the main factors of technology acceptance, such as EoU and U, and its impact on SS.

The data were collected via a survey method with a sample (n=112) of full-time undergraduate students at Kadir Has University. The researcher received 103 responses with a response rate of 92%.

Table 3.4). All were hypothesized to directly affect students' e-learning acceptance and indirectly student success.

The researcher chose IE205 (Technical Drawing) and GE204 (Probability and Statistics for Engineers) courses to conduct the research. IE205 was designed to introduce undergraduate students to the fundamental engineering drawing methods and computer-aided drafting of engineering drawings, where AutoCAD 2017 software was adapted for use by 49 students who installed it on their laptops to do weekly online assignments that they needed to upload through Khas Learn. The grading policy for this course is as follows: projects (30%), online midterm exam (30%), and online final exam (40%). GE204 covered topics related to probability and statistics for engineers and was taught to 78 undergraduate students. The grading policy for this course is as follows: five paper assignments (10%), two online midterm exams (40%), an online final exam (45%), and (5%) for online class participation.

Table 3.1 Source of Questionnaire Statements (SS & TAM & Factors)

Factors	Variables	Questionnaire Statements	Source of Statements
Students' Success (SS)	*SS1*	I am confident about my knowledge of the subject that I learned through (Khas Learn)	Developed by researcher
	SS2	I will get better marks when the course is taught online than in the classroom	Developed by researcher
	SS3	Online courses provided an easier balance between education, family, work, and COVID-19 pandemic safety requirements	(May, 2019)
	SS4	I feel I am better able to engage and interact with the course material (content) in online courses	(May, 2019)
	SS5	I am learning the course contents better when they are taught online than when they are taught in the classroom	(Alawamleh et al., 2020)
Perceived Usefulness (U)	*U1*	Online courses in (Khas Learn) improve my learning performance	(Binyamin et al., 2020); (Pituch & Lee, 2006)
	U2	Online courses in (Khas Learn) help me learn effectively	(Binyamin et al., 2020)
	U3	Using the (Khas Learn) increases my productivity in learning	(Abbad et al, 2009); (Davis 1986); (Pituch & Lee, 2006)
Perceived Ease of Use (EoU)	*EoU1*	Getting information from the Online Courses in (Khas Learn) was easy	(Abbad et al, 2009); (Davis 1986); (Pituch & Lee, 2006)
	EoU2	I have no trouble in using (Khas Learn) to perform tasks that I needed	(Cho et al., 2009)

	EoU3	The (Khas Learn) provides information that is easy to comprehend	(Cho et al., 2009)

Table 3.2 Source of Questionnaire Statements (Self-Assessment factor)

Factors	Variables	Questionnaire Statements	Source of Statements
Self-Efficacy (SE)	*SE1*	I am confident using the (Khas Learn) even if there is no one around to show me how to do it	(Tan and Teo, 2000); (Abbad et al, 2009); (Pituch & Lee, 2006)
	SE2	I learned how to use (Khas Learn) online courses easily.	(Binyamin et al., 2018)
	SE3	I feel confident using (Khas Learn) online-teaching contents.	(Chang et al., 2011); Liaw (2008)

Table 3.3 Source of Questionnaire Statements (HCI Factors - Perceived Interface Design)

Factors	Variables	Questionnaire Statements	Source of Statements
Visual Design (VD)	*VD1*	Text, colors, and layout used in (Khas Learn) are consistent	(Binyamin et al., 2020)
	VD2	Text and graphics of (Khas Learn) are readable	(Binyamin et al., 2020)
	VD3	The interface design of (Khas Learn) is attractive to me	(Binyamin et al., 2020)
Course Environment (CE)	*CE1*	The course webpage on (Khas Learn) was helpful in active learning, critical thinking development, idea sharing, and contextual learning	Developed by resercher
	CE2	The course webpage on (Khas Learn) assisted in self-directed work with the possibility of receiving feedback regardless of time and place	Developed by resercher
Content Quality (CQ)	*CQ1*	Overall, the content of (Khas Learn) is up to date	(Binyamin et al., 2020)
	CQ2	Overall, the content of (Khas Learn) is organized in a logical sequence	(Binyamin et al., 2020)
	CQ3	Overall, there is sufficient content in (Khas Learn) to support my learning	(Binyamin et al., 2020)
System Quality (SQ)	*SQ1*	The (Khas Learn) is fun to operate and subjectively pleasing	(Lin, 2010)
	SQ2	I am satisfied with (Khas Learn) functions	(Liaw, 2008); (Chang et al., 2011)
	SQ3	I can gain access to any course materials in (Khas Learn) without much effort	Kim and Lee, (2014)

The data required in this research need an appropriate tool, as well as a survey technique to collect respondents' perceptions based on the Five-Likert Scale about the interface and interactivity of the web-based teaching. It is also necessary to examine the correlation of these factors with the main factors of technology acceptance, such as EoU and U, and its impact on SS.

The data were collected via a survey method with a sample (n=112) of full-time undergraduate students at Kadir Has University. The researcher received 103 responses with a response rate of 92%.

Table 3.4 Source of Questionnaire Statements (HCI Factors - Perceived Interactivity)

Factors	Variables	Questionnaire Statements	Source of Statements
Learner-Interface Interactivity (LInt)	*LInt1*	Students can use (Khas Learn) map to locate their needed information.	(Chou, 2003)
	LInt2	Students can track their status regarding their grade points or relative status in a class.	(Chou, 2003)
	LInt3	Students can access online teaching materials anytime they want	Developed by resercher
	LInt4	I can start using (Khas Learn) easily with some online help	(Binyamin et al., 2020)
	LInt5	The (Khas Learn) enable students to accomplish course tasks more quickly	(Lin, 2010)
Navigation (Nav)	*Nav1*	The navigational structure of (Khas Learn) is convenient for me	(Binyamin et al., 2020)
	Nav2	It is easy for me to find the information I need in (Khas Learn)	(Binyamin et al., 2020)
	Nav3	Links in (Khas Learn) are working satisfactorily	(Binyamin et al., 2020)
Accessibility and Technical Support (AcS)	*AcS1*	E-mail enquiries can be made when there is a technical problem with (Khas Learn)	(Abbad et al, 2009)
	AcS2	The online help of (Khas Learn) is always available	(Binyamin et al., 2020)
	AcS3	The (Khas Learn) manual provides the information I need	(Binyamin et al., 2020)
	AcS4	It is easy for me to login to (Khas Learn)	(Binyamin et al., 2020)
	AcS5	I can access (Khas Learn) from different browsers	(Binyamin et al., 2020)
	AcS6	The pages and other elements of (Khas Learn) download quickly	(Binyamin et al., 2020)
Course Evaluation's System (CES)	*CES1*	(Khas Learn) provides good online self-assessment tools (e.g., online exams, quizzes, or assignments)	(Binyamin et al., 2020)

	CES2	The assessment tools (e.g., online exams, quizzes, or assignments) in (Khas Learn) measure my achievements of the course learning objectives	(Binyamin et al., 2020)
	CES3	I received useful feedback on my performance about online assignments and exams	Developed by researcher
Course Structure and Content (CSC)	*CSC1*	The online course content is consistent with the course objectives	Developed by researcher
	CSC2	I am confident that I will complete the knowledge or skill presented in this online course	Developed by researcher
	CSC3	The online course was organized in a manner that helped me understand the underlying concepts	Developed by researcher

3.5.1 Survey validity and reliability:

Various statistical tools and features included in SPSS were employed to investigate and analyze the factors that influence e-learning acceptance. The validity of survey contents was reviewed by a group of experts and proven by testing a pilot conducted with a thirty participant who was not involved in the process of actual data collection. Then, the survey reliability was tested by using Cronbach's alpha method which ranged from 0.733 to 0.911, bigger than 0.70 for all factors in the model (Table 3.5), while the variable (CE3) was excluded from the calculations because it did not exceed the Cronbach's alpha test. Thus, the research tool is considered reliable.

Table 3.5 Reliability Static of Factors Influencing E-learning Acceptance and SS (Survey1)

Factor	Variables	Cronbach's Alpha
Students' Success (SS)	SS1, SS2, SS3, SS4, SS5	0.859
Usefulness (U)	U1, U2, U3	0.911
Ease to Use (EoU)	EoU1, EoU2, EoU3	0.751
Self-Efficacy (SE)	SE1, SE2, SE3	0.774
Visual Design (VD)	VD1, VD2, VD3	0.817
Course Environment (CE)	CE1, CE2	0.753
Content Quality (CQ)	CQ1, CQ2, CQ3	0.737
System Quality (SQ)	SQ1, SQ2, SQ3	0.780
Learner-Interface Interactivity (LInt)	Lint1, Lint2, Lint3, Lint4, Lint5	0.733
Navigation (Nav)	Nav1, Nav2, Nav3	0.735
Accessibility and Support (A&S)	AcS1, AcS2, AcS3, AcS4, AcS5, AcS6	0.748

Course Evaluations' System (CES)	CES1, CES2, CES3	0.806
Course Structure and Content (CSC)	CSC1, CSC2, CSC3	0.797

Furthermore, exploratory factor analysis was employed with 0.9 as the Eigenvalue to be sure about the reliability of the strength of the factors. Then, eight factors were extracted after conducting (Principal Component Analysis and Varimax with Kaiser Normalization Rotation). The eight factors were course evaluation system (CSE), visual design (VD), content quality (CQ), navigation (Nav), course structure and content (CSC), learner-interface interactivity (LInt), course environment (CE), and system quality (SQ). Each categorized factor consists of 2 to 5 items out of 25 (Table 3.6).

The analysis extracted an eight-factor solution, each with Eigenvalues above 0.9, which explains 75.11% of the total variance. While Kaiser-Meyer-Olkin which sampling adequacy (Sharma & Alvi, 2021) was (KMO=0.842), and indicated a meritorious level, the Bartlett's test for sphericity was statistically significant ($\chi 2$ = 1613.684, p = 0.000), verifying that correlations between variables were sufficiently large to justify principal components analysis.

Table 3.6 Rotated Component Matrix *a*

Component								
Variable	1	2	3	4	5	6	7	8
CES2	0.856							
CES3	0.718						0.401	
CES1	0.480				0.362		0.317	
VD2		0.881						
VD1		0.790						
VD3		0.788						
CQ1			0.794					
CQ2			0.727		0.360		0.319	
CQ3			0.554		0.427			0.387
Nav2	0.377			0.578		0.307		
Nav3	0.546			0.546		0.398		
Nav1	0.496			0.507				
CSC2					0.835			
CSC3	0.405				0.757			
CSC1					0.681			0.344
LInt4						0.839		
LInt3						0.761		

LInt2						0.659		
LInt5			0.354			0.624		
LInt1			0.390			0.494		0.329
CE2	0.328						0.700	
CE1	0.302	0.389					0.623	
SQ3						0.389		0.690
SQ2	0.310	0.459	0.398					0.535
SQ1		0.447	0.402					0.461
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.								
a. Rotation converged in 9 iterations.								

3.6 Results

The data collected via survey and analyzed by SPSS indicate that all statements are significant, and the inter-items are correlated.

3.6.1 Demographic and descriptive statistics:

The highest percentage of participants were males (74.8%), aged between 21-25 years old (82.5%), studying for three years at the university (42.7%), increased their GPAs from 2.00 to 2.49 (35.9%), and from 2.50 to 2.99 (30.1%), enrolled in GE204 course (53.4%), and expected to get BB (33.0%) and or AB (31.1%) grade letter (Table 3.7).

Table 3.7 Personal Information (Survey Part One)

Personal Information		**Frequency**	**Percent**
Gender	Male	77	74.8%
	Female	26	25.2%
	Total	103	100%
Age	18-20	18	17.5%
	21-25	85	82.5%
	Total	103	100%
Academic Year	2 years	23	22.3%
	3 years	44	42.7%
	4 years or more	36	35.0%
	Total	103	100%
GPA	1.99 or less	8	7.8%
	2.00-2.49	37	35.9%
	2.50-2.99	31	30.1%
	3.00-3.49	17	16.5%
	3.50 or grater	10	9.7%

	Total	103	100%
The course registered	GE204	55	53.4%
	IE205	33	32.0%
	GE204 & IE205	15	14.6%
	Total	103	100%
The expected letter grade for the course	AA	21	20.4%
	BA	32	31.1%
	BB	34	33.0%
	CB	10	9.7%
	CC	4	3.9%
	DC	2	1.9%

The results of short questions about technology usage in online courses show that 37.9% of the students spend between 4-6 hours on the internet per day; and 48.5% spend between 4-6 hours per week in their studies; 51.5% use from 5 to 8 platforms or tools; 87.4% use laptops to connect to Khas Learn while around 38% use SMART phones, 33% use desktops, or around 6% use tablets (Table 3.8).

Table 3.8 Technology Usage (Survey Part Two)

Technology Usage		**Frequency**	**Percent**
Device used to connect Khas Learn	SMART Phone	39	37.9%
	Laptop	90	87.4%
	Desktop	34	33.0%
	Tablet	6	5.8%
Number of platforms, applications, or tools used in the course which web-based	1-4	26	25.2%
	5-8	53	51.5%
	9-12	19	18.4%
	13-16	5	4.9%
The daily time spent on the internet	1-3 hr.	36	35.0%
	4-6 hr.	39	37.9%
	7-9 hr.	17	16.5%
	over 9 hr.	11	10.7%
	Total	103	100%
The weekly time spent on the online course	1-2 hours	21	20.4%
	3-4 hours	50	48.5%
	5-6 hours	18	17.5%
	7 hours or more	14	13.6%
	Total	103	100%

To prove the effectiveness of e-learning, and its impact on SS, short questions were prepared, and students' courses grades were calculated. The results show that 82.5% of students considered the use of Khas Learn made them safe and secure; 66.0% prefer online o face-to-face learning; 36.9% expected their grades in the courses taught online;

and 59.2% got grades in these courses greater than their GPA; besides, 24.3% got equal marks to their GPA (Table 3.9).

Table 3.9 Online Course Outcomes (Survey Part Three)

Personal Information		Frequency	Percent
Using Khas Learn makes me safe and secure.	Yes	85	82.5%
	No	6	5.8%
	I do not know	12	11.7%
	Total	103	100%
Preferring online to face to face learning	Yes	68	66.0%
	No	25	24.3%
	I do not know	10	9.7%
	Total	103	100%
Course grade as expected	Yes	38	36.9%
	No	65	63.1%
	Total	103	100%
Course grade equal or greater than student's GPA	Greater	61	59.2%
	Equal	25	24.3%
	Lower	17	16.5%
	Total	103	100%

3.6.2 Hypotheses testing

Furthermore, all hypotheses derived from integrated HCI factors with TAM factors and the integration of all these factors with SS were supported and proven to be significant determinants (Table 3.10). And the coefficient of determination of SS in the proposed conceptual model is 54.9% (adjusted R^2=0.549), where U is the strongest determinant of SS.

3.6.2.1 Student success result

The results of linear regression analysis of hypotheses show that SS is jointly predicted by U (ρ=0.736, P<0.01), and EoU (ρ=0.476, P<0.01). The factors are as follows: U explain 54.1% (R^2=0.541); and EoU explain 22.7% (R^2=0.227) of the variance of SS (Table 3.10), where R^2 represents the coefficient of determination and ρ represents the coefficient of correlation. So, H1 and H2 were supported.

3.6.2.2 Perceived usefulness results

The results of multi-linear regression analysis (Table 3.10) show that U is jointly predicted by VD, CE, CQ, and SQ (ρ=0.564, P<0.01). These interface design factors explain U by 31.9% (adjusted R^2=0.319), where SQ is one of the strongest determinants of U. Thus, ***H6*** was supported. In addition, the EoU is one of the main predictors of U (R^2=0.242, ρ=0.492). So, ***H3*** was supported. Furthermore, U is jointly predicted by LInt, Nav, CES, and CSC (ρ=0.604, P<0.01) excluding accessibility and technical support (AcS), which has a very weak positive effect on U (ρ=0.181, P>0.05). These interactivity factors explain U by 36.5% (adjusted R^2=0.365), where CES is the strongest determinant of Perceived Usefulness. Thus, ***H8*** was supported.

3.6.2.3 Perceived ease of use results

The results of multi-linear regression analysis (Table 3.10) show that EoU is jointly predicted by VD, CE, CQ, and SQ (ρ=0.491, P<0.01). These interface design factors explain EoU by 24.1% (adjusted R^2=0.241), where CE is the strongest determinant of EoU. Thus, ***H7*** was supported. Furthermore, EoU is jointly predicted by LInt, Nav, AcS, CES, and CSC (ρ=0.625, P<0.01). These interactivity factors explain EoU by 39.1% (adjusted R^2=0.391), where CES is the strongest determinant of EoU. Thus, ***H9*** was supported.

3.6.2.4 Self-efficacy results

Hypothesis test results (Table 3.10) show that SE has a very weak positive effect on U (ρ=0.078, P>0.05), while it has a significant positive effect on EoU (ρ=0.404, P<0.01). This factor explains 16.3% variance of EoU (R^2=0.163). Thus, ***H4*** and ***H5*** were supported.

Table 3.10 Hypotheses Testing Results (Linear and Multi-Linear Regression Tests)

Hypotheses	Regression	R^2	(ρ) Pearson Corr.	Type of Corr.	P-Value	Support
H1	U → SS	.541	.736**	+	.000	Yes
H2	EoU → SS	.227	.476**	+	.000	Yes
H3	EoU → U	.242	.492**	+	.000	Yes

H4	SE → U	.006	.078	+	.431	Yes
H5	SE→ EoU	.163	.404**	+	.000	Yes
H6	VD → U	.094	.306**	+	.002	Yes
	CE → U	.192	.438**	+	.000	
	CQ → U	.115	.339**	+	.000	
	SQ → U	.246	.496**	+	.000	
	(VD, CE, CQ, SQ) → U	.319	.564**	+	.000	
H7	VD → EoU	.042	.205*	+	.038	Yes
	CE → EoU	.185	.431**	+	.000	
	CQ → EoU	.166	.408**	+	.000	
	SQ → EoU	.095	.307**	+	.002	
	(VD, CE, CQ, SQ) → EoU	.241	.491**	+	.000	
H8	LInt → U	.133	.365**	+	.000	Yes
	Nav → U	.192	.438**	+	.000	
	AcS → U	.033	.181	+	.067	
	CES → U	.248	.498**	+	.000	
	CSC → U	.175	.418**	+	.000	
	(LInt, Nav, AcS, CES, CSC) → U	.365	.604**	+	.000	
H9	LInt → EoU	.154	.393**	+	.000	Yes
	Nav → EoU	.264	.513**	+	.000	
	AcS → EoU	.128	.358**	+	.000	
	CES → EoU	.287	.536**	+	.000	
	CSC → EoU	.242	.492**	+	.000	
	(LInt, Nav, AcS, CES, CSC) →EoU	.391	.625**	+	.000	

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

3.6.2.5 Mediation results

Mediation analysis was conducted to assess the mediating role of U on the linkage between EoU and SS. The hypothesis test results (Table 3.11) show that the total effect of the EoU on SS was significant (β=.599, P<0.01), where β represents the coefficients of the mediation model. With the inclusion of the mediating U factors, the impact of the EoU on SS was still found significant (β=.410, P<0.01). The indirect effect of the EoU on SS through U was found insignificant (β=.189, P>0.05).

These results show that the relationship between the EoU and SS is completely mediated by U. Moreover, the explained variance of SS by EOU was 22.7% (R^2=0.227), while the addition of U resulted in a substantial jump in the explained variance to 55.8% (R^2=0.558). Thus, ***H10*** was supported.

Table 3.11 Hypotheses Testing Results (Mediation Tests)

Hypotheses	Regression	Effect	Coeff.	P-Value	Support
H10	**U** mediate	EoU → U	.662**	.000	Yes
	EoU→SS	EoU → SS	.599**	.000	Complete
		EoU+U→SS			Mediation
		U→SS	.619**	.000	
		EoU → SS	.189	.051	
		Indirect eff.	.410**	.000	
			CI		
			[.235,.614]		
			R^2 = .558		

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

3.6.2.6 Moderation results

The moderation test (Table 3.12) through the macro-PROCESS for SPSS provided by Hayes (2013) presents two models that can be added to previous models related to linearity and nonlinearity. The first model (X+M→Y) explains the dependent factor (EU or U) with two predictors: HCI factor (X), and moderator (M). The second model (Int-I.(X*M)+X+M→Y) explains the dependent factors with three predictors: HCI factor (X), moderator (M), and the interaction term between one of the HCI factors and moderator. The test (Table 3.12) showed that gender moderated only the relationship between VD and EOU (R^2=.112, P<0.01) for the model where the change is in R^2=0.061, b=-.673, P<0.05 for the integration, and between CE and EoU (R^2=.270, P<0.01) for the model where change is in R^2=0.041, b=-.607, P<0.05 for the integration, and b represents the coefficients of the moderation model.

Furthermore, test (Table 3.12) showed that GPA moderated only the relationship between Nav and U (R^2=.270, P<0.01) for the model where change is in R^2=0.037, b=-.297, P<0.05 for the integration, between SQ and EoU (R^2=.136, P<0.01) for the model where change is in R^2=0.041, b=-.176, P<0.05 for the integration, and between Nav and EoU (R^2=.298, P<0.01) for the model where change is in R^2=0.030, b=-.198, P<0.05 for the integration.

Besides, test (Table 3.12) showed that using a SMART phone to connect to Khas Learn moderated only the relationship between CQ and EoU (R^2=.205, P<0.01) for the model where change is in R^2=0.038, b=.490, P<0.05 for the integration, and between CE and EoU (R^2=.219, P<0.01) for the model where change is in R^2=0.032, b=-.417, P<0.05 for the integration.

Moreover, the test (Table 3.12) showed that the daily time a student spends on the internet moderated only the relationship between CQ and U (R^2=.159, P<0.01) for the model where change is in R^2=0.039, b=-.390, P<0.05 for the integration; and the weekly time a student spends on online studying moderated only the relationship between CQ and U (R^2=.414, P<0.01) for the model where change is in R^2=0.054, b=-.417, P<0.05 for the integration.

While test (Table 3.12) showed that students' web-based activities during learning process (Logs) moderated only the relationship between CE and U (R^2=.245, P<0.01) for the model where change is in R^2=0.052, b=-.001, P<0.05 for the integration, between CQ and U (R^2=.173, P<0.01) for the model where change is in R^2=0.041, b=-.002, P<0.05 for the integration, and between CES and EoU (R^2=.362, P<0.01) for the model where change is in R^2=0.074, b=-.001, P<0.05 for the integration.

Accordingly, the empirical data partially supported ***H11***, which referred to prior gender as a moderator of the influence of VD or CE on EoU; and to prior GPA as a moderator of the influence of Nav on U or EU, and SQ on EU. And the empirical data partially supported ***H12***, which referred to prior SMART phone usage as a moderator of the influence of CQ or CE on EoU; and to prior the time spent on the internet or studying online as a moderator of the influence of CQ on U. Also, the empirical data partially supported ***H13***, which referred to prior student web-based activities during the learning process as a moderator of the influence of CE or CQ on U, or CES on EoU.

Table 3.12 Hypotheses Testing Results (Moderation Tests)

Hypotheses	**Regression**	**Model X+M→Y**	**Int-I. X*M**	**Strong Effect**	**Support**

H11	Gender moderate	*p-value*	*R^2 change* *b = Effect*		Yes Partially
	VD → EoU	R^2=.112, P=.008	R^2=.060, *b*= -.673*, P=.011	Male R^2=.095	
	CE → EoU	R^2=.230, P=.000	R^2=.041, *b*= -.605*, P=.023	Male R^2=.255	
	GPA moderate Nav → U	R^2=.270, P=.000	R^2=.037, *b*=-.297*, P=.028	GPA<2 R^2=.409 73.8%<.85	
	SQ → EoU	R^2=.136, P=.002	R^2=.041, *b*=-.176*, P=.033	GPA<2 R^2=.335 73.8%<.71	
	Nav→ EoU	R^2=.298, P=.000	R^2=.030, *b*=-.198*, P=.044	GPA<2 R^2=.885 90.2%<1.17	
H12	SMART Phone use moderate CQ→ EoU	R^2=.205, P=.000	R^2=.038, *b*=.490*, P=.031	Yes R^2=.398	Yes Partially
	CE→ EoU	R^2=.219, P=.000	R^2=.032, *b*=-.417*, P=.046	No R^2=.276	
	Daily time on internet moderate CQ→ U	R^2=.159, P=.007	R^2=.039, *b*=-.390*, P=.035	1-3 hr. R^2=.319 **72.8%<2.53**	
	Weekly time online study moderate CQ→ U	R^2=.414, P=.000	R^2=.054, *b*=-.417*, P=.013	1-2 hr. R^2=.318 **68.9%<2.76**	
H13	Logs moderate CE → U	R^2=.245, P=.000	R^2=.052, *b*=-.001*, P=.011	Logs<502.5 76.7%<1097.3	Yes Partially
	CQ → U	R^2=.173, P=.003	R^2=.041, *b*=-.002*, P=.011	Logs<502.5 61.2%<932.8	
	CES → EoU	R^2=.362, P=.000	R^2=.074, *b*=-.001*, P=.001	Logs<502.5 79.6%<1158.3	

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

3.6.3 Conceptual model testing results

Based on the testing results of all hypotheses, the researcher determined the conceptual model as a framework for the effect of human-computer interaction on e-learning acceptance and student success called e-LASS (Figure 3.4).

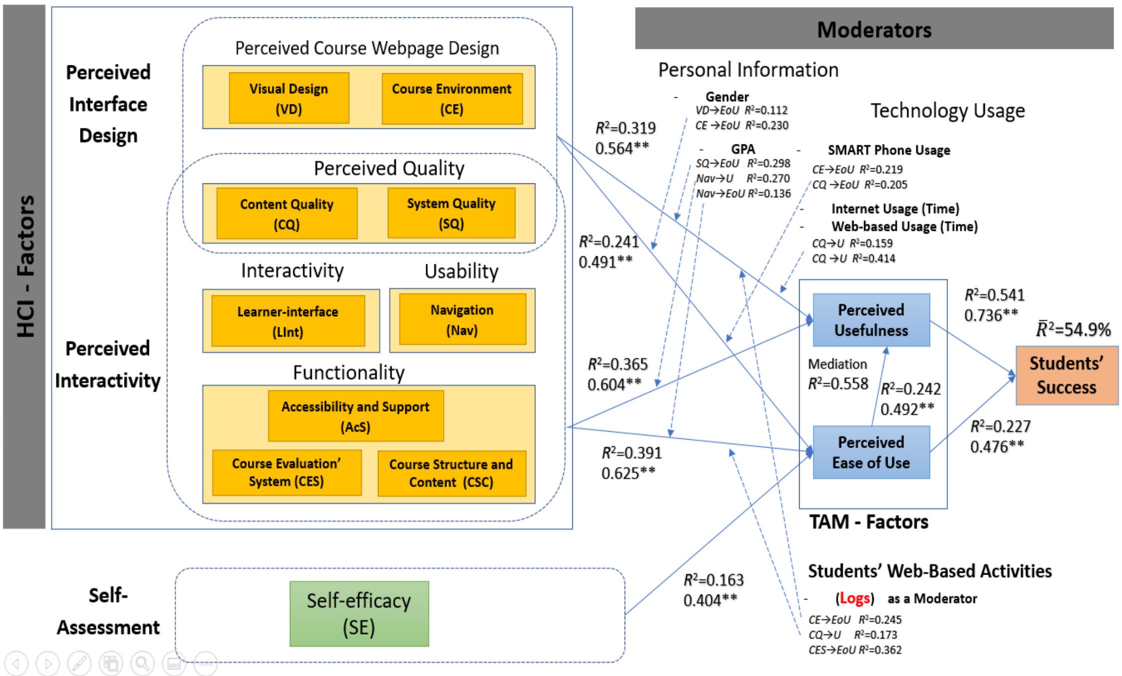

Figure 3.4 The researcher's conceptual model (e-LASS)

3.6.4 Statistical differences among participants

To understand the differences in perceptions across different student groups, they were classified into two layers based on their ages and courses they registered for. The researcher used the independent sample *t*-test method at the ($P < 0.05$) level of significance.

The analysis (Table 3.13) shows that there are statistical differences among participants, who were grouped into two ages. The students aged between 21-25 years old are more likely to rate SQ ($P<0.05$, $d=0.67$, $Mean=3.71$) and SS ($P<0.05$, $d=0.61$, $Mean=3.62$) than those aged within 18-20, where the effect size (Cohen's d) of older students is classified medium.

Table 3.13 Statistical Differences According to Age (t-Test for Equality of Means)

Independent Samples Test								
Factor	t	df	Sig.	Mean		Mean Diff.	Effect Size	Effect
				18-20	21-25		Cohen's *d*	Type

SQ	-2.599	101	0.011	3.20	3.71	-0.51	0.67	Medium
SS	-2.367	101	0.020	3.02	3.62	-0.60	0.61	Medium

In addition, the analysis (Table 3.14) shows that there are statistical differences among participants who registered for two courses taught online. The students who registered in the course IE205 are more likely to rate CE (P<0.05, d=0.55, *Mean* =4.08), LInt (P<0.05, d=0.60, *Mean* =4.16), Nav (P<0.05, d=0.60, *Mean* =4.18), CES (P<0.05, d=0.45, *Mean* =3.97), and U (P<0.05, d=0.52, *Mean* =3.22) than who registered in the course GE204.

Table 3.14 Statistical Differences According to Course (t-Test for Equality of Means)

Independent Samples Test

Factor	t	df	Sig.	Mean		Mean Diff.	Effect Size	Effect
				GE	IE		Cohen's *d*	Type
CE	-2.507	86	0.014	3.69	4.08	-0.38	0.55	Medium
LInt	-2.705	86	0.008	3.78	4.16	-0.38	0.60	Medium
Nav	-2.728	86	0.008	3.79	4.18	-0.39	0.60	Medium
CES	-2.029	86	0.046	3.58	3.97	-0.39	0.45	Medium
U	-2.340	86	0.022	3.22	3.77	-0.54	0.52	Medium

Furthermore, the data were collected and classified in three intervals, or more were tested by One-Way ANOVA test to check even if there were statistical differences among participants. Then, the Post Hoc tests (LSD) tool was employed in a way to detect the main difference (Table 3.15). The test shows differences among students concerning their academic years and expected grades in courses to be (P<0.05).

Table 3.15 Statistical Differences between Groups According to Academic Years and Grades (Post Hoc Test – LSD)

Factor	**CE**			**SQ**			**CQ**			**CSC**		
Variable	*F*	*sig.*	η^2	*F*	*sig.*	η^2	*F*	*sig.*	η^2	*F*	*sig.*	η^2
Academic Year	3.41	0.04	0.06									
Course Grade				5.63	0.01	0.1	5.36	0.01	0.1	4.53	0.01	0.08

Factor	**CES**			**U**			**SS**			**AcS**		
Variable	*F*	*sig.*	η^2	*F*	*sig.*	η^2	*F*	*sig.*	η^2	*F*	*sig.*	η^2
Academic Year				3.35	0.04	0.06	8.79	0.00	0.15			
Course Grade	7.1	0.00	0.12	3.69	0.03	0.07	6.42	0.00	0.11	4.89	0.01	0.09

Students who are in the 4th or higher academic year are more likely to rate usefulness (Table 3.16) than those who are in the 2nd or 3rd academic year (P<0.05, P<0.05, η^2=0.063, *Mean*=3.81). And the students who are in the 3rd or higher academic year are more likely to rate SS (P<0.05, P<0.05, η^2=0.150, *Mean*=3.92, 3.51) than those who are in the 2nd academic year. Eta-square (η^2) represents the effect size.

Table 3.16 Statistical Differences According to Academic Year (LSD Test)

Dependent Variable	(I)	(J)	Mean Difference (I-J)	Sig.
CE	3 years	2 years	-.37500*	0.037
		4 years or more	-.34722*	0.027
U	4 years or more	2 years	.60266*	0.032
		3 years	.52525*	0.027
SS	2 years	3 years	-.62213*	0.010
		4 years or more	-1.03527*	0.000

* The mean difference is significant at the 0.05 level.

Students whose course grades are “equal” or “greater” (Table 3.17) are more likely to rate VD (P<0.05, P=0.001<0.05, η^2=0.101, *Mean*= 3.91, 3.96), CQ (P<0.05, P=0.003<0.05, η^2=0.097, *Mean*=3.92, 3.88), CSC (P<0.05, P<0.05, η^2=0.083, *Mean*=4.08, 4.14), CES (P<0.05, P=0.002<0.05, η^2=0.124, *Mean*=4.03, 3.81), AcS (P<0.05, P=0.003<0.05, η^2=0.089, *Mean*=4.11, 4.10), U (P<0.05, P<0.05, η^2=0.069, *Mean*=4.04, 4.00), and SS (P<0.05, P<0.05, η^2=0.114, *Mean*=3.66, 3.66) than those students whose course grade expectations are “lower”.

Table 3.17 Statistical Differences According to Course Grades Compared to GPA (LSD Test)

Dependent Variable	(I)	(J)	Mean Difference (I-J)	Sig.
SQ	"Lower"	"Equal"	-.58824*	0.013
		"Greater"	-.67567*	0.001
CQ	" Lower"	"Equal"	-.58275*	0.004
		"Greater"	-.51302*	0.003
CSC	" Lower"	"Equal"	-.49176*	0.022
		"Greater"	-.54838*	0.004
CES	" Lower"	"Equal"	-.92863*	0.000
		"Greater"	-.71070*	0.002
U	" Lower"	"Equal"	-.73647*	0.026
		"Greater"	-.75024*	0.010

SS	" Lower"	"Equal"	-.89929*	0.003
		"Greater"	-.89759*	0.001
AcS	" Lower"	"Equal"	-.44667*	0.008
		"Greater"	-.43169*	0.003

* The mean difference is significant at the 0.05 level.

3.6.5 Correlations among grouped factors

To uncover the bivariate relationships between grouped independent key factors, we should initially consider whether the Pearson correlation is appropriate or whether we should turn to Spearman if there are violations of the assumptions. Pearson’s correlations assumptions tests were examined to assess the normality, linearity, outliers (Obilor & Amadi, 2018), homoscedasticity, and independence were violated (Schober et al., 2018). The Pearson's correlation is used to quantitatively describe the degree of relationship between two continuous variables that are normally distributed (Hu et al., 2021). For the five Likert-scale, the observed variables are ordinal; in some schools of thought, they have treated each item as ordinal where the choices are arranged in ranking order, while others have considered as interval estimates if items are combined to generate a composite score for a set of items (Joshi et al., 2015). Hence, the factors calculated from these variables in this study on the basis of calculating the mean are treated as continuous, regardless of their categorical nature (Rhemtulla et al., 2012). Thus, this data set can be processed statistically using Pearson's correlation coefficient (Joshi et al., 2015).

For normality, the values of skewness and kurtosis should be acceptable (Heilala et al., 2022), as being in the range of -3 to +3 for studies with 50 to 300 participants, according to Salami et al. (2020); in the range of -2 to +2, according to Allan (2016), George and Mallery (2010); or in the range of -1 to +1, according to Hair et al. (2017). The assumption of normality was confirmed through the normality test, where the values of skewness for all the variables ranged between -1 and +1, and the values of kurtosis <3 (Table 3.18), exhibiting that distribution of data was normal.

To test linearity and homoscedasticity, the paired independent factors were plotted in a scatterplot and analyzed for any potential patterns in the data points. By visually examining the shape of the graph, it was seen that there was a linear component of association between the tested constructs. The patterns which indicate heteroscedasticity were noted. This means that the variances along the fit line are not similar to those moving along the line (Salami et al., 2020). Furthermore, outliers were checked using boxplots, and serious violations were noted, which means there was a single data point or more within observations that did not follow the usual pattern (Obilor & Amadi, 2018) as "individual outliers would have strongly affected the outcome" (Murmann & Karegar, 2021). So, the examinations indicated there were violations of Pearson's correlation assumptions.

Table 3.18 Descriptive and Normality Statistics for the Study Constructs

Construct	Mean	Std. Deviation	Skewness	Kurtosis
Visual Design	3.89	0.71	-0.54	1.45
Course Environment	3.83	0.71	-0.12	-0.35
System Quality	3.62	0.77	-0.61	0.59
Content Quality	3.92	0.65	-0.17	-0.20
Learner-Interface Interactivity	3.97	0.65	-0.95	2.78
Navigation	3.97	0.67	-0.38	0.28
Course Structure and Content	4.03	0.69	-0.47	-0.02
Course Evaluation System	3.74	0.86	-0.54	0.14
Self-Efficacy	4.42	0.53	-0.37	-0.75
Usefulness	3.45	1.06	-0.61	-0.13
Ease to Use	3.95	0.79	-0.75	0.39
Student Success	3.51	0.99	-0.24	-0.91
Accessibility and Support	4.03	0.55	-0.13	-0.36

Consequently, we tested the Spearman correlation of rank variables, which is a nonparametric correlation for a measure of monotonic relationship (Shaikh & Barbé, 2019; Cavallo, 2019). Spearman's correlation coefficients are a measure of the direction and the strength of association that exists between two variables. Either data ordinal or continuous data violate the assumptions necessary for testing the Pearson's correlation (Balacco et al., 2022; Chok, 2010), considered as an alternative.

The results show that (Table 3.19) significant positive monotonic correlations exist among all independent factors EoU and U (*P*<0.01, *rho*=0.492**).

Table 3.19 Spearman's Correlation Coefficients among TAM Main Factors and SS

Factor	Correlation	U	EoU	SS
U	Spearman's rho	1	.492**	.729**
	Sig. (2-tailed)		0.000	0.000

EoU	Spearman's rho	1	.492**
	Sig. (2-tailed)		0.000
SS	Spearman's rho		1
	Sig. (2-tailed)		

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

Besides, the results show that (Table 3.20) significant positive monotonic correlations exist among all independent factors associated with HCI interface design, with the strongest correlation between VD and SQ (*P*<0.01, *rho*=0.595**).

Table 3.20 Spearman's Correlation Coefficients among HCI Interface Design Factors

Factor	Correlation	VD	CE	SQ	CQ
VD	Spearman's rho	1	.489**	.595**	.447**
	Sig. (2-tailed)		0.000	0.000	0.000
CE	Spearman's rho		1	.421**	.482**
	Sig. (2-tailed)			0.000	0.000
SQ	Spearman's rho			1	.571**
	Sig. (2-tailed)				0.000

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

Furthermore, the results show that (Table 3.21) positive monotonic significant correlations exist among all independent factors associated with HCI interactivity, with the strongest correlation between Nav and LInt (*P*<0.01, *rho*=0.595**), and between Nav and AcS (*P*<0.01, *rho*=0.593**).

Table 3.21 Spearman's Correlation Coefficients among HCI Interactivity Factors

Factor	Correlation	LInt	Nav	CSC	CES	AcS
LInt	Spearman's rho	1	.595**	.452**	.479**	.548**
	Sig. (2-tailed)		0.000	0.000	0.000	0.000
Nav	Spearman's rho		1	.493**	.572**	.521**
	Sig. (2-tailed)			0.000	0.000	0.000
CSC	Spearman's rho			1	.530**	.593**
	Sig. (2-tailed)				0.000	0.000
CES	Spearman's rho				1	.545**
	Sig. (2-tailed)					0.000

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

3.7 Discussion

Our study suggests that e-learning acceptance and student success (e-LASS) can serve as the starting point for the generalization of TAM extended by HCI in other contexts. The model explained approximately 54.9% of the variance of users' perceived success after they accepted e-learning technology, taking into consideration the presence of online experience as students' activity "Logs" and time spent online studying or using the internet as a moderator of the relationships between HCI constructs and EoU or U to visit irrespective of the levels of gender and GPA as a moderator.

Although around 66% of the students' GPAs were in the middle, more than 64% expected to get a high-grade letter in the online courses they were enrolled in, which indicates their conviction of the feasibility of e-learning in achieving success. And the majority of students considered using "Khas Learn" safe and secure. Also, they preferred online learning to face-to-face learning. This means they are convinced of achieving success that practically translated to higher marks in the online courses than their GPAs.

The vast majority of students use laptops to connect to Khas Learn, while nearly a third use smartphones. The statistics of TurkStat (2020) indicate the proportion of availability of such devices until 2020 in the household as mobile phones (incl. smartphone) (99.4%); portable computers (laptop, netbook) (36.4%); tablet computers (22%); and desktop computers (16.7%). This strengthens the importance of studying the adaptation of university system applications used in e-learning, for smart devices as well as tablets, to increase e-learning acceptance, and then succeed through promoting HCI.

3.7.1 Hypotheses testing discussion

All hypotheses are supported and significant at 99%. This indicates that all results are logical and can be adopted where the constructs of the developed model explain 54.9% of the variance of student success (adjusted R^2=0.549).

As two independent factors (U, EoU) are predictors of the SS, where the U was the highest contributor (54.1%), and completely mediates the relationship between the EU and SS. In addition, EU is one of the main predictors of U. Respondents' beliefs about their success are related to being confident about knowledge of the subject that they learned through Khas Learn (mean=3.77). Getting better marks when the course is taught online than taught in the classroom: (mean=3.21). The ability of easier balance between education, family, work, and COVID-19 pandemic safety requirement: (mean=3.91). The better engagement and interaction with the course materials and contents in online courses: (mean=3.75). Learning course contents better when they are taught online than taught in the classroom: (mean=2.93). These results are somewhat consistent with Huffman and Huffman (2012), who revealed that student success in their courses more likely relies on technology usage if their perception of the ease of use and the usefulness of the use of technology that matches the instructors' expectations are high. And it is consistent with Ifinedo et al. (2018), who found that Moodle acceptance of the main constructs represented by U and EoU "have a significant positive effect on students' assessment of its use outcomes" (Ifinedo et al., 2018), which were (ρ =0.62) like students' success in this study were (ρ =0.73).

Perceived U and EoU are predicted by nine independent factors, out of which four interface design constructs came; namely, VD, CE, CQ, and SQ in terms of both; four interactivity constructs; namely, LInt, Nav, CES, and CSC in terms of both; in addition to EoU in terms of U while AcS in terms of EoU. These results are consistent with some of Binyamin's (2019) findings where he tested the effect of some HCI constructs as the main component of system development processes aimed at improving system facilities and ensuring that users' needs are satisfied (Al Mahdi et al., 2019). These common constructs are CO, Nav, and AcS, where the latter is considered the weakest. But the difference in the two studies is about the effect of VD, wherein Binyamin et al. (2019) the assessment disclosed the lack of this relationship with TAM, while this study's findings reveal a weak positive effect on U or EoU. For system designers, HCI can help with identifying the needs that include and can provide: good online self-assessment tools (mean=3.90) that measure users' achievements of the course learning objectives (mean=3.68), useful feedback on their performance about online assignments and exams (mean=3.65), fun to operate with subjectively pleasing tools (mean=3.29), and satisfied with functions (mean=3.65), accessible course materials without much effort (mean=3.92), a helpful design in active learning and critical thinking development (mean=3.79), assistance in self-directed work with the possibility of receiving feedback regardless of time and place (mean=3.87), a convenient navigational structure (mean=3.89), which makes it easier to find the information the users need in the system (mean=4.02), links that work satisfactorily (mean=4.01), and an online course organized in a manner that helps understand the underlying concepts (mean=3.87). The CES, SQ, CE, Nav, and CSC are the highest contributors to explaining the (24.8%, 24.6%, 19.2%, 19.2%, and 17.5%, respectively) variance of U, and the CES, Nav, CSC, CE, and CQ are the highest contributors for explaining the (28.7%, 26.4%, 24.2%, 18.5%, and 16.6%, respectively) variance of EoU.

Compared to Abdullah and Ward (2016), the results show consistency with the generalization that SE has significant positive influences on the EoU (ρ=0.404 in this study, whereas the average is ρ=0.342 in 80% of the previous studies), while it has weak positive influences on U (ρ=0.078 in this study, whereas average is ρ=0.088 in 63% of the previous studies). According to previously reviewed studies, SE is a person's self-conviction that users possess the competence necessary to deal with the requirements of completing a particular task successfully (Kang et al., 2021). That is what the respondents indicated about their confidence in using the Khas Learn even if there is no one around to show them how to do it (mean=4.49), or how to use Khas Learn online courses easily (mean=4.48), hence they feel confident using Khas Learn online-teaching contents (mean=4.29).

Students' web-based activities in the e-learning system are considered an aspect of actual use of the system and interaction with it, which cannot be a good substitute for behavioral intention, according to Pal and Patra (2021), who posed a question about whether different educational activities or tasks undertaken by the students are suitable for them. In this study, the effect of the activities' characteristics was tested as a moderator based on the number of logs of those tasks and activities, especially since HCI factors focus on the technical side, and acceptance of technology focuses on the behavioral side and intentions. The results of this study indicate that the effect of CE and CQ on U, or CES on EoU is stronger and more important for students whose Logs<502.5, where it is the category of students with a grade of CC or below that are defined as "Fair" to "Fail" according to the academic credit system and evaluation at Kadir Has University (see Table A.2). This means including logs as a moderator would increase the explanatory power of the effect of HCI factors on e-learning acceptance and student success in the model.

Furthermore, while the moderating effect of gender is found to be significant, the effect of perceived course webpage design factors; namely, VD and CE on EOU is stronger and more important for male students (R^2=0.095, R^2=.255), respectively. The result is consistent with Pal and Patra's (2021) inclusion of gender as a moderator, where the effect has been greater for male students. Also, consistent with Binyamin (2019), who deduced that gender moderates only one relationship between CQ and EoU, it is stronger for males compared with female students. As such, this is what Goswami and Dutta (2016) came up with to after reviewing many previous studies in various fields concerned with gender as a moderator variable in technology acceptance as males are found to have a higher perception of U and EoU than females. So, including gender as a moderator would increase the explanatory power of the effect of HCI factors on e-learning acceptance and student success in the model. Consequently, understanding the differences between students in terms of gender toward computer technologies enables teachers to choose appropriate learning tools and processes for each male, or female and contributes to the technologies' advancements (Goswami & Dutta, 2016).

In addition, the moderating effect of GPA is found to be significant, where the effect of usability and perceived quality, as the effect of Nav on U, or SQ or Nav on EOU, is stronger and more important for students whose GPAs<2 (R^2=0.409, R^2=.335, R^2=.885), respectively. The result is consistent with Sitar-Tăut and Mican (2021), who proved the moderation effect of GPA on the relationship that links independent exogenous factors to the acceptance of technology but shows that students with higher GPAs feel more motivated to accept and use m-learning than students with lower GPAs. It means including GPA as a moderator would increase the explanatory power of the effect of HCI factors on e-learning acceptance and student success in the model.

In terms of technology usage, the moderating influence is found to be significant, where the effect of CQ on the EoU is stronger and more important for the students who use SMART phones (R^2=0.389) to access the system, while the effect of CE on the EoU is stronger and more important for not using a SMART phone (R^2=0.276). The effect of CQ on the U is stronger and more important for students who spend one to three hours using the internet daily (R^2=0.319), while the effect of CQ on the U is stronger and more important for students who spend one to two hours studying online weekly (R^2=0.318).

This means including SMART phone usage, the time using the internet daily, or the time spent online studying weekly as a moderator would increase the explanatory power of the effect of HCI factors on e-learning acceptance and student success in the model.

In addition, the study revealed that students over the age of twenty, or who are in the third academic year or higher, are rated the most to indicate their success. Also, they highly rated the system quality from the side of gaining access to any course materials without much effort, which makes it subjectively pleasing and satisfactory in terms of functionality. Or they were higher regarding course environment, as the instructional materials were helpful in critical thinking development, contextual learning, self-directed work, and increased learner knowledge and skills in the subject matter, which show a statistically significant difference from others. So, it becomes clear that experience plays an important role in enhancing their perceptions. Furthermore, the result indicates that the accumulation of experiences enabled students to distinguish the importance of e-learning and its impact on success. Moreover, the effect size of students who registered in the course IE205 is classified as medium. It was clear that IE205 depended on projects in the evaluation and was more interactive than GE204, which means that students regard learner-interface interactivity more highly. Learners can use a map to locate their needed information, track their status regarding their grade points in a class, and access online teaching materials anytime they want. Also, their perceptions were better regarding navigation structure, course evaluations system, and usefulness of using e-learning. Accordingly, the users were more comfortable interacting with the computer and its features due to the interactive nature of this course.

3.8 Conclusion

The acceptance of e-learning has become an important issue for any educational institution in the light of technological developments and recent outbreak of the COVID-19 pandemic. This study applied the TAM for explaining the key factors that affect students' behaviour in higher education in the context of human-computer interaction, acceptance of e-learning systems, and achieving success through web-based learning. Furthermore, it proves the influential variables like online activities as a moderator to some causal relations in the proposed model. As a result of surveying 103 undergraduate students as a case study, who used the "KHAS Learn" system, the most critical HCI factors, which interact with student success through using online learning systems, and influence ease of use and usefulness of e-learning, were identified. And logs which represent user activities via the system as a moderator was proven. Then, the researcher introduced a comprehensive conceptual model called "e-LASS," where the adjusted R^2 for the whole model is equal to 54.9%.

In general, the results of this research contribute to the existing literature of HCI, e-learning acceptance, and SS through the following: linking engineering and technical issues with social sciences; helping decision-makers and specialists enhance the user experience in terms of e-learning actual use and success from the user point of view, especially in the light of the COVID-19 pandemic; and highlighting the importance of technology acceptance factors in enhancing student success, not solely their intention and attitudes toward actual use of any web-based systems.

Furthermore, the findings revealed some points which should be considered. First, personal information and technology usage will moderate some relationship between HCI and ease of use and usefulness of e-learning while U mediates the relationship between EoU and SS. Second, perceived interface design (VD, CE, CQ, and SQ), perceived interactivity (LInt, Nav, AcS, CES, and CSC), and self-assessment (self-efficacy) factors will significantly affect the main TAM factors (EoU and U), which will predict the student success. Third, perceived usefulness from using e-learning is the main predictor in the model that explains 54.1% of the SS variation. Fourth, two relationships were affected by gender (VD or CE → EoU), which is more important for males; three relationships were affected by students' GPAs (Nav → EOU, SQ or Nav → EoU), which is more important for students whose GPAs were lower than 2; two relationships were affected by SMART phone usage (CQ or CE → EoU), which is more important for those who do not use it; one relationship was affected by daily time spent on the internet (CQ → U); and one relationship was affected by weekly time spent on the online study (CQ → U), which is more important for those who spend less than 3 hours online. This means including a moderator would increase the explanatory power of the model. Fifth, universities should pay more attention to some factors when dealing with students aged from 18-20, who attended less interactive courses, got grades lower than their GPA, who are in the second academic year or lower, and who rated variables less than others.

Finally, in the context of developed countries like Turkey, the HCI factors integrated with TAM factors provide practical implications to the decision-makers in institutions of higher education and engineering designers, to convince students to accept and use e-learning in an effective manner in their universities and succeed. So, the following recommendations should be included in their consideration: improving the attractiveness of the interface design of the e-learning system to increase perceived VD; enhancing the perceived system quality in a way to be fun in operating and subjectively pleasing; enhancing the web-based assessment tools like exams, quizzes, or assignments; developing technical online feedback about their performance, which were rated the lowest according to the students' perception.

4. NON-LINEAR RELATIONSHIPS

Exploring Non-Linear Relationships between Perceived Interactivity or Interface Design and Acceptance of Collaborative Web-Based Learning

The novelty of this part of the study is in developing a conceptual model for predicting the non-linear relationships between human-computer interaction factors and ease of use and usefulness of a collaborative web-based learning or e-learning. Ten models (logarithmic, inverse, quadratic, cubic, compound, power, s-curve, growth, exponential, and logistic) were examined as functions of effects compared to linear relationships to see which was the most appropriate, based on R^2, adjusted R^2 and SEE values. To answer the addressed questions, the researcher surveyed 103 students from Kadir Has University about the perceived interface and interactivity of e-learning. The results show that most of the hypotheses formulated for this purpose have been proven. Analysis shows that cubic models (drawing the relationship between ease of use and usefulness, visual design, course environment, learner-interface interactivity, and course evaluation system and ease of use), quadratic models (drawing the relationship between visual design, and system quality and usefulness, course structure and content, course environment, and system quality and ease of use), logarithmic model (drawing the relationship between course evaluation system and usefulness), and s-curve models (learner-interface interactivity, navigation, and course structure and content and usefulness) performed better in the description for the correlations.

4.1 General Problem Statement and the Second Part Objectives

Most of the educational institutions including universities have resorted to providing most of their transactions and services online. Due to the rapid spread of the COVID-19 pandemic, the tremendous technological advancements, and the need to maintain education's continuity and activate the role of the parties in the educational process at the lowest costs, understanding the core knowledge of HCI fields in the interface design and interactivity aspects must be considered carefully to explore non-linear relationships with the level of e-learning acceptance from the students' point of view, which has not been previously tested.

Non-linear regression analysis is performed to model the pattern of changes in the resulting attribute based on changes in the calculated value of the factorial property. Either linear, quadratic, cubic, or logarithmic equations might be considered after the statistical significance; and the determination coefficients of the models are calculated (Zakrizevska-Belogrudova & Sevcenkova, 2020). Hence, nonlinear modelling enables the accurate reflections of the real nature of main developmental phenomena that lead to powerful heuristic outcomes, integrating and summarising knowledge, and constructing the basis for detailed causal relations and process models afterwards (Bervell et al., 2020).

Building on the argument of non-linear relationships, Sekulić et al. (2005) stated that non-linear results give more explanations about the great proportion associated with common variance compared to linear regression results. In some cases, it was proven that the non-linear relationship could clarify the real nature of the ratios among the variables. Later, this was confirmed by Bervell and Umar (2017) where they pointed out that the practical application of non-linear correlations supports the emergence types of great fundamental proportions of variance that it represented.

Furthermore, when the effects across a range of values are constant, it is considered a linear effect. If the effects are not constant across the values of the independent variable, it is considered a nonlinear effect. That is because of the nature of the independent variable or due to the specification of the predictor, regardless of whether it is a transformation of a continuous or a categorical outcome. But this does not mean that a linear effect in regression models cannot be non-linear. The relationships in the dependent variables that are categorical in the natural metric of the predicted variable always have a non-linear relationship, and this is in contrast to the linear relationships in the linear regression models (Mize, 2019).

Hakami (2018) claim that “in the natural and behavioural phenomena, most of the relationships between the variables are nonlinear, but usually it is a u-shaped curve or inverted u-shaped curve.” So, this study aims to

- Examine if a non-linear relationship exists between the main factors of human-computer interaction and ease of use and usefulness of collaborative web-based learning.
- Test the level of variance (R^2), which explains the percentage of the accuracy of the independent variables; perceived interface design, interactivity, and course design, in determining the dependent variable; perceived ease of use and usefulness for collaborative web-based learning when non-linear correlations between HCI factors and TAM main factors are modelled.

4.2 Research Model and Hypotheses Development

The researcher presented a conceptual model (Figure 4.1) to test non-linear relationships between HCI factors with ease of use and usefulness of e-learning at Kadir Has University, from the viewpoint of the students who are engaged in an online learning system. Also, the aim was to investigate if respondent characteristics moderate these relations.

4.2.1 TAM main factors

A variety of research projects were conducted, and linear regression analyses were employed to prove the EoU and U relationship (Venkatesh, 2000; Venkatesh and Davis, 2000; AL-Ammari and Hamad, 2008; Venkatesh and Bala, 2008; Phua et al., 2012). But non-linearity was not investigated. Hence, the researcher developed hypotheses as follows:

Hypothesis 1: Perceived ease of use will have a non-linear relationship with usefulness in collaborative web-based learning.

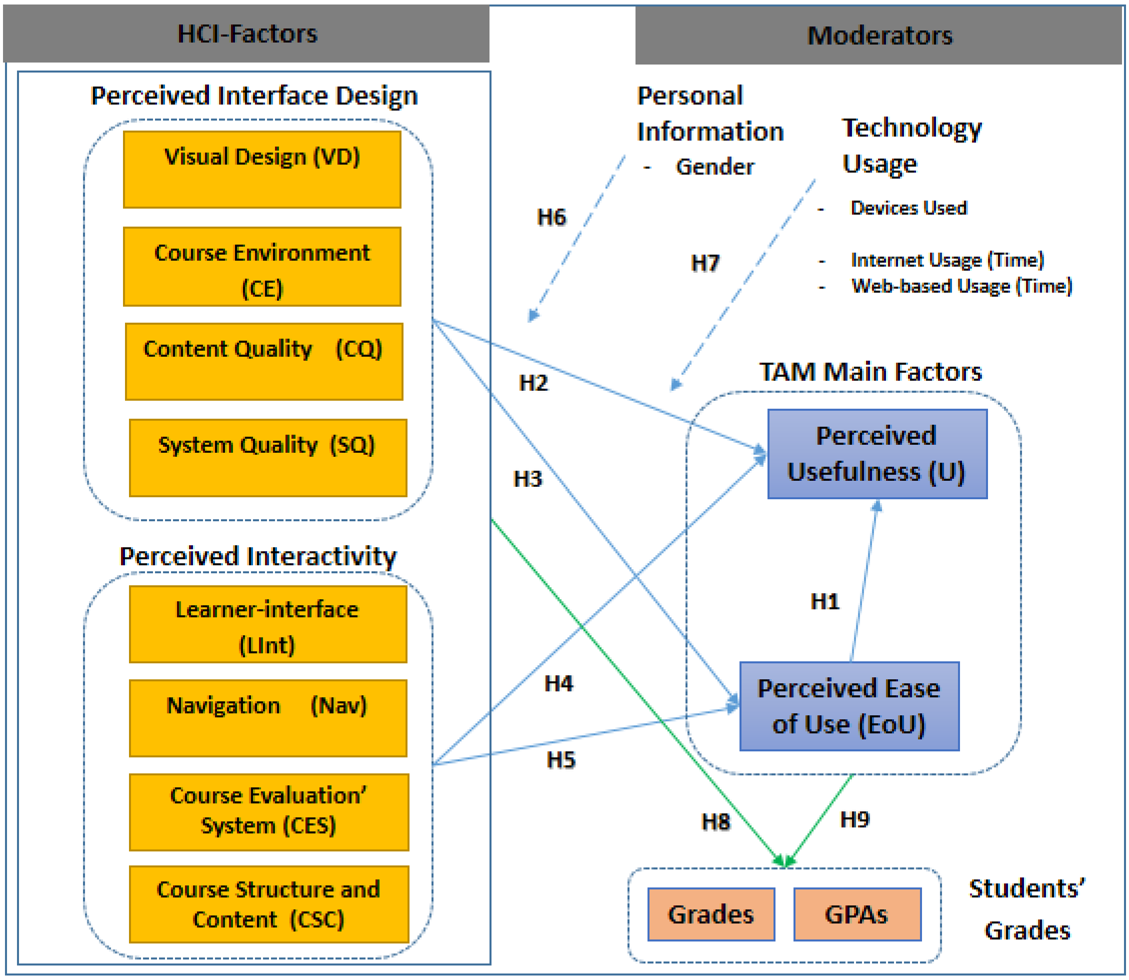

Figure 4.1 The researcher's proposed conceptual model

4.2.2 HCI main factors

According to Issa and Isaias (2015), the main factors and issues embedded in interaction and interactivity, and hence included in HCI design need to be considered by HCI specialists to achieve a user-friendly and safe system. They are organizational, environmental, health and safety components, users, comfort, task, constraints, system functionality, and productivity factors.

From organizational factors, which cover job design, politics, and work organization that affect content quality, we derived these variables (see **Table A.1**): CQ1=overall, the content of (Khas Learn) is up to date; CQ2=is organized in a logical sequence; CQ3=and is sufficient to support learning.

From environmental factors, which cover noise, heating, lighting, ventilation, time limitations, whether they are technical aspects or content aspects related to the courses (Veglis & Barbargires, 2001), we derived these variables: CE1=the course webpage on (Khas Learn) was helpful in active learning, critical thinking development, idea sharing, and contextual learning; CE2=assisted in self-directed work with the possibility of receiving feedback regardless of time and place.

From health and safety factors, during the COVID-19 pandemic, we derived these variables: (v1=using Khas Learn makes me safe and secure, and v2=preferring online to face to face learning).

From the user motivation, satisfaction, personality, enjoyment, and experience level associated with the system quality, we derived these variables: SQ1=the (Khas Learn) is fun to operate and subjectively pleasing, SQ2=its functions satisfactory, SQ3= and the course materials are accessible without much effort.

From comfort factors, output displays, dialogue structures, graphics, color, commands, icons, natural language, multi-media, and user support materials that can be described as visual design, we derived these variables: VD1=text, colors, and layout used in (Khas Learn) are consistent; VD2=text and graphics are readable; VD3=and the interface design is attractive.

From user interface interactivity that considers the dialogue structures, output displays, input device, icons, multi-media, and navigation, we derived these variables: LInt1=students can use (Khas Learn) map to locate their needed information; Lint2=track their status regarding their grade points or relative status in a class; LInt3=access online teaching materials anytime they want; LInt4=start the use easily with some online help; LInt5=and accomplish course tasks more quickly. Nav1=the navigational structure of (Khas Learn) is convenient for the students; Nav2=easy to find the information they need; Nav3=and its links are working satisfactorily.

From task factors related to some characteristics such as task allocation, monitoring, and components, and the degree of their consideration like novel, easy, complex, and repetitive, we derived these variables: EoU1=getting the information from the Online Courses in (Khas Learn) was easy; EoU2=without trouble to perform tasks needed; EoU3=and the system provides information that is easy to comprehend.

From system functionality, whether related to software, hardware, or application, we derived these variables, which can be determined through course structure and content or course evaluation's system: CSC1=the online course content is consistent with the course objectives; CSC2=the students are confident that they will complete the knowledge or skill presented in the online course; CSC3=which was organized in a manner that helped them understand the underlying concepts; CES1=and (Khas Learn) provides good online self-assessment tools such as online exams, quizzes, or assignments; CES2=which measure the achievements of the course learning objectives; CES3=and send back useful feedback on performance about online assignments and exams).

From productivity factors, which can be expressed by increasing the output, quality, creativity and generating innovative ideas, we derived these variables: U1=Online Courses in (Khas Learn) improves learning performance; U2=helps to learn effectively; U3=and increases productivity in learning.

To investigate the importance of enhancing the users' perceived interface design in achieving a friendly, simple, functional, and free effort system of e-learning, and to test whether there is a non-linear relationship between the interface design and technology acceptance factors, the researcher developed hypotheses as follows:

Hypothesis 2: VD, CE, CQ, and SQ will have a non-linear relationship with students' perceived usefulness of collaborative web-based learning.

Hypothesis 3: VD, CE, CQ, and SQ will have a non-linear relationship with students' perceived ease of use of collaborative web-based learning.

To test the effects of enhancing the perceived interactivity of students on raising the acceptance of e-learning and the non-linearity relationship between these factors, the researcher developed hypotheses as follows:

Hypothesis 4: LInt, Nav, CES, and CSC will have a non-linear relationship with student's perceived usefulness of collaborative web-based learning.

Hypothesis 5: LInt, Nav, CES, and CSC will have a non-linear relationship with student's perceived ease of use of collaborative web-based learning.

4.2.3 Moderating effects

The importance of the moderation test is to provide empirical evidence of variables in which the U or EoU, and interactivity or interface design relationships, become stronger or weaker, particularly among students where their characteristics may play a major role in modifying the traditional relationship of the dependent and independent variables (Sugianto, 2017). In the first part of this study, we studied the effect of the GPA as a moderator, and the results were surprising. Furthermore, we tried to discover a linear relationship between the model constructs and the GPA as an outcome, but no linear relationship was proven. So, in this part of the research, we tried to find if a nonlinearity detects a link between HCI or TAM main factors and GPA. In the light of these potential variables that would increase the explanatory power of the EoU and U as a moderator, the researcher developed hypotheses as follows:

Hypothesis 6: Personal information (gender) moderates the positive effect of perceived interface design factors (VD, CE, CQ, SQ, LInt, Nav, CES, and CSC) on the students' perceived usefulness or ease of use of collaborative web-based learning.

Hypothesis 7: Technology usage (devices used, times, and internet usage) moderates the positive effect of perceived interactivity factors (VD, CE, CQ, SQ, LInt, Nav, CES, and CSC) on the students' perceived usefulness or ease of use of collaborative web-based learning.

4.2.4 Students' academic outcomes (GPAs and course grades)

The students' outcomes represent the students' academic performance in terms of their GPAs (grade point average), which was measured in this study based on a ratio scale for students' cumulative grades in previous semesters, and their grades (Madigan & Curran, 2021) in the courses. These were obtained via collaborative web-based learning, which was accessible to the researcher at the end of the semester, where respondents' names were anonymous. One of our concerns in this study is correlated with the student outcomes as engagement in collaborative web-based learning if affected by HCI main factors or enhanced by users' perceptions at a specific level of achievement. So, this was the question: did participation in collaborative web-based learning cause enhancement in students' academic performance? In other words, do they earn higher GPAs or higher grades in their courses when they interact with e-learning systems, and at any level of interaction with the system or at any level of perceived ease of use of the system or the perceived usefulness?

As far as we know, there is a scarcity of studies that have tested the effect of technology acceptance or interaction factors on student achievement. In this study, a non-linear assumption is required if the linear assumption does not answer this question, whereas the nonlinearity test may lead to a result that differs from linearity ones, according to Kock (2016). Hence, the researcher developed hypotheses as follows:

Hypothesis 8: HCI main factors will have a non-linear relationship with students' GPAs or grades in courses delivered via collaborative web-based learning.

Hypothesis 9: Perceived ease of use or usefulness will have a non-linear relationship with students' GPAs or grades in courses delivered via collaborative web-based learning.

4.3 Methodology

In first part of this study, two approaches have been integrated during hypothesis validation and data collection. First, the qualitative method by reviewing literature ad conducting a semi-structured questionnaire for the grounded theory (GT) analysis. Here, GT is a systematic approach that aims to construct theories grounded in the data (Holt et al., 2022), in a context of theoretical sampling that prioritized implementing the main constructs of the proposed conceptual model. Second, the primary data were collected via survey in order to test the effect of the constructs that were derived in the proposed model. The secondary data was collected by extracting the students' grades from the university Moodle "Khas Learn." Finally, it was collected by developing a conceptual model using linear and non-linear regression analyses.

4.3.1 Data analysis:

The data collected has been analyzed, evaluated, and compared to explore the non-linear correlation between independent and dependent factors associated with HCI and e-learning acceptance. The researcher followed these steps in conducting the analysis process: applying a statistical package for the social sciences (SPSS-v25) as proper software useful for getting the causal relationships between questionnaire elements and fit with the quantitative approach; using the frequency's percentages of participants to present personal information, and technology experiences; outlining the statistical differences among participants by conducting independent sample t-test and one-way ANOVA test; and determining which of the hypotheses will be supported, through using curve estimation analysis. ANOVA was used to analyze the variance and explore the relationship between constructs (in linear and nonlinear regression analysis), which is a powerful tool for determining the influence of independent variables on the dependent variable. The final step is developing a conceptual model that predicts the non-linearity based on three measures and then modelling the size of the non-linear correlation effect.

A nonlinear regression analysis will be conducted based on estimated coefficients that derived from the best fit curve for the data when using the curve estimation function in SPSS (Keum, 2019; Tesfaye, 2019).

4.4 Findings and Discussion

4.4.1 Hypothesis testing

The researcher used one linear and ten non-linear (logarithmic, inverse, quadratic, cubic, compound, power, S, growth, exponential, and logistic equations as shown in Table 4.1 regression techniques to model the relationships between HCI main factors and TAM main factors. Each of these equations denoted a candidate as the best function model for the relationship between factors based on three measures (Quadri, 2019). The values of (R^2) represent the coefficient of determination; values of (adjusted R^2) represent the adjusted coefficient of determination as part of the total variance explained by the model; and values of (SEE), which represents the standard error of estimate that provides information about the precision of estimates and the prediction errors' dispersion in the regression analysis. In all, for the statistical significance, the researcher used the confidence level ($p < 0.05$).

Table 4.1 Curve estimation regression models

Equation Type	Model Form	Code
Linear	Y = b0 + (b1 * t)	1
Logarithmic	Y = b0 + (b1 * ln(t))	2
Inverse	Y = b0 + (b1 / t)	3
Quadratic	Y = b0 + (b1 * t) + (b2 * t**2)	4
Cubic	Y = b0 + (b1 * t) + (b2 * t**2) + (b3 * t**3)	5
Compound	Y = b0 * (b1**t) or ln(Y) = ln(b0) + (ln(b1) * t)	6
Power	Y = b0 * (t**b1) or ln(Y) = ln(b0) + (b1 * ln(t))	7
S	Y = e**(b0 + (b1/t)) or ln(Y) = b0 + (b1/t)	8
Growth	Y = e**(b0 + (b1 * t)) or ln(Y) = b0 + (b1 * t)	9
Exponential	Y = b0 * (e**(b1 * t)) or ln(Y) = ln(b0) + (b1 * t)	10
Logistic	Y = 1 / (1/u + (b0 * (b1**t))) or ln(1/y-1/u) = ln (b0) + (ln(b1) * t)	11

Furthermore, Cohen (1988) classified the association strength in suggested guidelines as a measure of effect size, which is based on the coefficient of correlation (r) or the coefficient of determination (R^2). Cohen's guidelines, which were presented in Table 4.2, indicate that a correlation is "trivial" when it is less than 0.1, a correlation is "small" when it is within [0.1 and 0.3), a correlation is "medium" when it is within [0.3 and 0.5), and a correlation is "large" when it is 0.5 or greater. Also, the equivalent ranges for R^2 are given in Table 4.2 as follows: The size of correlation effect is "small" when R^2 is within [0.01 and 0.09), which means between 1% to 8% of the variance is shared; the size of correlation effect is "medium" when R^2 is within [0.09 and 0.25), which means between 9% to 24% of the variance is shared; and the size of correlation effect is "large" when R^2 is 0.25 or greater, which means at least 25% of the variance is shared.

4.4.1.1 Perceived usefulness and perceived ease of use relationship

Collected data by a survey was entered into SPSS-v25 software to draw a correlation by conducting curve estimation analysis for estimating the effect of perceived ease of use as an independent factor on perceived usefulness as a dependent factor. The results show that linear and non-linear correlations were proven, and the equations were derived from this formation to compare the appropriateness of correlation based on (R^2, R^2_{adj}, and SEE). For linear regression, R^2 is equal to 0.242, R^2_{adj} is equal to 0.235, and SEE is equal to 0.929 (β=0.492, F=32.313, p<0.05); and for non-linear regression R^2 is equal 0.273, R^2_{adj} is equal to 0.251, and SEE is equal to 0.919 for cubic curve (F=12.382, p<0.05). Accordingly, the cubic non-linear relationship between EU and U would provide a more accurate result than a linear and other non-linear relationship since higher $R^2$and R^2_{adj} and lower SEE values indicate a better function. So, ***H1*** is supported. Also, the obtained value for R^2 of the cubic model is 0.273 (Table 4.3), which concludes that the size of a correlation had a "large" effect.

Table 4.2 Guidelines from Cohen (1988) for classifying the size of correlation effect

| r |	R^2	Size of Effect
0.1 ≤ | r | < 0.3	$0.01 \leq R^2 < 0.09$	Small
0.3 ≤ | r | < 0.5	$0.09 \leq R^2 < 0.25$	Medium
| r | ≥ 0.5	$R^2 \geq 0.25$	Large

The selected cubic regression function is:

$$U = -7.597 + (8.918 * EoU) + (-2.51 * EoU^2) + (.241 * EoU^3) \qquad (4.1)$$

Table 4.3 Model statistics and parameter estimates of the fitted models (EoU→U)

Model	Model Statistics			Parameter Estimates			
	R^2	R^2 (adj)	SEE	b0	b1	b2	b3
Linear	.242	.235	.929	.831	.662		
Logarithmic	.236	.229	.933	.432	2.233		
Inverse	.218	.211	.943	5.216	-6.627		
Quadratic	.243	.228	.933	1.257	.416	.034	
Cubic	.273	.251	.919	-7.597	8.918	-2.510	.241
Compound	.196	.188	.358	1.343	1.249		
Power	.206	.198	.355	1.128	.779		
S	.207	.199	.355	1.817	-2.412		
Growth	.196	.188	.358	.295	.222		
Exponential	.196	.188	.358	1.343	.222		
Logistic	.196	.188	.358	.744	.801		

4.4.1.2 Visual design and TAM main factors (U and EoU) relationships

The result of estimating the effect of visual design on perceived usefulness show that linear and non-linear correlations were proven. For linear regression R^2 is equal to 0.094, R^2_{adj} is equal to 0.085, and SEE is equal to 1.016 (β=0.306, F=10.447, p<0.05); and for non-linear regression R^2 is equal 0.109 and 0.109, R^2_{adj} is equal to 0.082 and 0.091, and SEE is equal to 1.018 and 1.013 for cubic curve (F=4.017, p<0.05) and for quadratic curve (F=6.086, p<0.05), respectively. Accordingly, the quadratic non-linear relationship between VD and U would provide a more accurate result than a linear and other non-linear relationship since higher R^2 and R^2_{adj} and lower SEE values indicate a better function. So, ***H2*** $_{VD}$ is supported. Also, the obtained value for R^2 of the quadratic model is 0.109 (Table 4.4), which concludes that the size of a correlation had a "medium" effect.

The selected quadratic regression function is:

$$U = 3.595 + (-.625 * VD) + (.146 * VD^2) \qquad (4.2)$$

Table 4.4 Model statistics and parameter estimates of the fitted models (VD→U)

Model	Model Statistics			Parameter Estimates			
	R^2	R^2 (adj)	SEE	b0	b1	b2	b3
Linear	.094	.085	1.016	1.675	.456		
Logarithmic	.074	.065	1.027	1.623	1.363		
Inverse	.047	.037	1.042	4.281	-3.097		
Quadratic	.109	.091	1.013	3.595	-.625	.146	
Cubic	.109	.082	1.018	3.719	-.755	.187	-.004
Compound	.079	.070	.383	1.757	1.170		
Power	.061	.052	.386	1.740	.463		
S	.036	.027	.391	1.448	-1.021		
Growth	.079	.070	.383	.564	.157		
Exponential	.079	.070	.383	1.757	.157		
Logistic	.079	.070	.383	.569	.855		

The effect of visual design on perceived ease of use shows that linear and non-linear correlations were proven. For linear regression R^2 is equal to 0.042, R^2_{adj} is equal to 0.032, and SEE is equal to 0.777 (β=0.205, F=4.419, p<0.05); and for non-linear regression R^2 is equal 0.076, R^2_{adj} is equal to 0.048, and SEE is equal to 0.771 for cubic curve (F=2.712, p<0.05). Accordingly, the cubic non-linear relationship between VD and EoU would provide a more accurate result than a linear and other non-linear relationship since higher R^2 and R^2_{adj} and lower SEE values indicate a better function. So, ***H3*** $_{VD}$ is supported. Also, the obtained value for R^2 of the cubic model is 0.076 (Table 4.5), which concludes that the size of a correlation had a "small" effect.

The cubic regression function selected is:

$$EoU = 7.337 + (-3.268 * VD) + (.898 * VD^2) + (-.073 * VD^3) \quad (4.3)$$

Table 4.5 Model statistics and parameter estimates of the fitted models (VD→EoU)

Model	**Model Statistics**			**Parameter Estimates**			
	R^2	R^2 (adj)	SEE	b0	b1	b2	b3
Linear	.042	.032	.777	3.070	.227		
Logarithmic	.026	.017	.783	3.143	.604		
Inverse	.011	.001	.789	4.253	-1.120		
Quadratic	.070	.052	.769	5.050	-.888	.151	
Cubic	.076	.048	.771	7.337	-3.268	.898	-.073
Compound	.037	.027	.228	3.029	1.064		
Power	.023	.013	.230	3.096	.165		
S	.009	-.001	.231	1.430	-.296		
Growth	.037	.027	.228	1.108	.062		
Exponential	.037	.027	.228	3.029	.062		
Logistic	.037	.027	.228	.330	.940		

4.4.1.3 Course environment and TAM main factors (U and EoU) relationships

The result of estimating the effect of course environment on perceived usefulness show that linear and non-linear correlations were proven. For linear regression, R^2 is equal to 0.192, R^2_{adj} is equal to 0.184, and SEE is equal to 0.959 (β=0.438, F=23.995, p<0.05); and for non-linear regression, R^2 is equal 0.199, R^2_{adj} is equal to 0.183, and SEE is equal to 0.960 for cubic curve (F=12.409, p<0.05) and for quadratic curve (F=12.385, p<0.05). Accordingly, the cubic and quadratic non-linear relationship between CE and U would provide a more accurate result than a linear and other non-linear relationship since higher R^2 and R^2_{adj} and lower SEE values indicate a better function. So, ***H2**$_{CE}$* is supported. Also, the obtained value for R^2 of the cubic and quadratic models are 0.199 (Table 4.6), which concludes that the size of a correlation had a "medium" effect.

The selected quadratic and cubic regression functions are, respectively:

$$U = -.982 + (1.700 * CE) + (-.137 * CE^2) \quad (4.4a)$$

$$U = 2.072 + (-.926 * CE) + (.589 * CE^2) + (-.065 * CE^3) \quad (4.4b)$$

Table 4.6 Model statistics and parameter estimates of the fitted models (CE→U)

Model	Model Statistics			Parameter Estimates			
	R^2	R^2 (adj)	SEE	b0	b1	b2	b3
Linear	.192	.184	.959	.921	.659		
Logarithmic	.197	.189	.956	.227	2.430		
Inverse	.194	.186	.958	5.698	-8.309		
Quadratic	.199	.183	.960	-.982	1.700	-.137	
Cubic	.199	.183	.960	2.072	-.926	.589	-.065
Compound	.164	.156	.365	1.351	1.256		
Power	.170	.161	.363	1.058	.843		
S	.168	.160	.364	1.956	-2.888		
Growth	.164	.156	.365	.301	.228		
Exponential	.164	.156	.365	1.351	.228		
Logistic	.164	.156	.365	.740	.796		

The effect of course environment as on perceived ease of use shows that linear and non-linear correlations were proven. For linear regression, R^2 is equal to 0.185, R^2_{adj} is equal to 0.177, and SEE is equal to 0.716 (β=0.431, F=23.001, p<0.05); and for non-linear regression R^2 is equal 0.187, R^2_{adj} is equal to 0.171, and SEE is equal to 0.719 for cubic curve (F=11.485, p<0.05). Accordingly, the cubic non-linear relationship between CE and EoU would provide a more accurate result than a linear and other non-linear relationship since higher R^2 and R^2_{adj} and lower SEE values indicate a better function. So, ***H3$_{CE}$*** is supported. Also, the obtained value for R^2 of the cubic model is 0.187 (Table 4.7), which concludes that the size of a correlation had a "medium" effect.

The selected cubic regression function is:

$$EoU = 11.717 + (-7.928 * CE) + (2.364 * CE^2) + (-.214 * CE^3) \qquad (4.5)$$

Table 4.7 Model statistics and parameter estimates of the fitted models (CE→EoU)

Model	Model Statistics			Parameter Estimates			
	R^2	R^2 (adj)	SEE	b0	b1	b2	b3
Linear	.185	.177	.716	2.105	.391		
Logarithmic	.182	.174	.718	1.647	1.739		
Inverse	.169	.161	.724	5.513	-5.763		
Quadratic	.186	.170	.720	1.634	.740	-.034	
Cubic	.187	.171	.719	11.717	-7.928	2.364	-.214
Compound	.180	.172	.210	2.265	1.149		
Power	.182	.174	.210	1.969	.508		
S	.172	.164	.211	1.812	-1.703		
Growth	.180	.172	.210	.818	.139		
Exponential	.180	.172	.210	2.265	.139		
Logistic	.180	.172	.210	.442	.870		

4.4.1.4 Content quality and TAM main factors (U and EoU) relationships

The result of estimating the effect of content quality on perceived usefulness show that linear and non-linear correlations were proven. For linear regression, R^2 is equal to 0.115, R^2_{adj} is equal to 0.106, and SEE is equal to 1.004 (β=0.339, F=13.151, p<0.05); and for non-linear regression R^2 is equal 0.116, R^2_{adj} is equal to 0.098, and SEE is equal to 1.009 for cubic curve (F=6.529, p<0.05) and for quadratic curve (F=6.529, p<0.05). Accordingly, the linear relationship between CQ and U would provide a more accurate result than a non-linear relationship since higher R^2_{adj} and lower SEE values indicate a better function. So, $\boldsymbol{H2_{CQ}}$ is not supported. Also, the obtained value for R^2 of the linear model is 0.115 (Table 4.8), which concludes that the size of a correlation had a "medium" effect.

The selected linear regression function is:

$$U = 1.263 + (.558 * CQ) \tag{4.6}$$

Table 4.8 Model statistics and parameter estimates of the fitted models (CQ→U)

Model	Model Statistics			Parameter Estimates			
	R^2	R^2 (adj)	SEE	b0	b1	b2	b3
Linear	.115	.106	1.004	1.263	.558		
Logarithmic	.112	.103	1.005	.671	2.055		
Inverse	.106	.097	1.009	5.322	-7.129		
Quadratic	.116	.098	1.009	1.751	.297	.034	
Cubic	.116	.098	1.009	2.540	-.357	.210	-.015
Compound	.108	.099	.377	1.469	1.223		
Power	.106	.097	.377	1.180	.746		
S	.100	.091	.378	1.855	-2.595		
Growth	.108	.099	.377	.384	.201		
Exponential	.108	.099	.377	1.469	.201		
Logistic	.108	.099	.377	.681	.818		

The effect of content quality on perceived Ease of Use shows that linear and non-linear correlations were proven. For linear regression, R^2 is equal to 0.166, R^2_{adj} is equal to 0.158, and SEE is equal to 0.725 (β=0.408, F=20.171, p<0.05); and for non-linear regression R^2 is equal 0.167, R^2_{adj} is equal to 0.150, and SEE is equal to 0.728 for cubic curve (F=9.990, p<0.05). Accordingly, the linear relationship between CQ and EoU would provide a more accurate result than a non-linear relationship since higher R^2_{adj} and lower SEE, and a slight difference of R^2 values indicate a better function. So, $\boldsymbol{H3_{CQ}}$ is not supported. Also, the obtained value for R^2 of the linear model is 0.166 (Table 4.9), which concludes that the size of a correlation had a "medium" effect.

The selected linear regression function is:

$$EoU = 1.999 + (.499 * CQ) \tag{4.7}$$

Table 4.9 Model statistics and parameter estimates of the fitted models (CQ→EoU)

Model	Model Statistics			Parameter Estimates			
	R^2	R^2 (adj)	SEE	b0	b1	b2	b3
Linear	.166	.158	.725	1.999	.499		
Logarithmic	.164	.156	.726	1.455	1.848		
Inverse	.156	.148	.729	5.648	-6.447		
Quadratic	.166	.150	.728	1.895	.554	-.007	
Cubic	.167	.150	.728	7.633	-4.208	1.273	-.112
Compound	.163	.155	.212	2.192	1.155		
Power	.165	.157	.212	1.854	.543		
S	.163	.154	.213	1.857	-1.924		
Growth	.163	.155	.212	.785	.144		
Exponential	.163	.155	.212	2.192	.144		
Logistic	.163	.155	.212	.456	.866		

4.4.1.5 System quality and TAM main factors (U and EoU) relationships

The result of estimating the effect of system quality on perceived usefulness shows that linear and non-linear correlations were proven. For linear regression R^2 is equal to 0.246, R^2_{adj} is equal to 0.238, and SEE is equal to 0.927 (β=0.496, F=32.918, p<0.05); and for non-linear regression R^2 is equal 0.267 and 0.267, R^2_{adj} is equal to 0.245 and 0.252, and SEE is equal to 0.923 and 0.918 for cubic curve (F=12.012, p<0.05) and for quadratic curve (F=18.200, p<0.05), respectively. Accordingly, the quadratic non-linear relationship between SQ and U would provide a more accurate result than a linear and other non-linear relationship since higher R^2 and R^2_{adj} and lower SEE values indicate a better function. So, ***H2$_{SQ}$*** is supported. Also, the obtained value for R^2 of the quadratic model is 0.267 (Table 4.10), which concludes that the size of a correlation had a "large" effect.

The selected quadratic regression function is:

$$U = 2.906 + (-.523 * SQ) + (.178 * SQ^2) \tag{4.8}$$

Table 4.10 Model statistics and parameter estimates of the fitted models (SQ→U)

Model	Model Statistics			Parameter Estimates			
	R^2	R^2 (adj)	SEE	b0	b1	b2	b3
Linear	.246	.238	.927	.975	.683		
Logarithmic	.214	.207	.946	.929	1.998		
Inverse	.174	.166	.970	4.944	-5.103		
Quadratic	.267	.252	.918	2.906	-.523	.178	
Cubic	.267	.245	.923	2.974	-.591	.199	-.002
Compound	.221	.213	.352	1.347	1.273		
Power	.202	.194	.356	1.296	.725		
S	.173	.164	.363	1.729	-1.896		
Growth	.221	.213	.352	.298	.242		
Exponential	.221	.213	.352	1.347	.242		
Logistic	.221	.213	.352	.742	.785		

The effect of system quality on perceived ease of use shows that linear and non-linear correlations were proven. For linear regression, R^2 is equal to 0.095, R^2_{adj} is equal to 0.086, and SEE is equal to 0.755 (β=0.307, F=10.544, p<0.05); and for non-linear regression R^2 is equal 0.168 and 0.167, R^2_{adj} is equal to 0.142 and 0.151, and SEE is equal to 0.732 and 0.728 for cubic curve (F=6.645, p<0.05) and for quadratic curve (F=10.054, p<0.05), respectively. Accordingly, the quadratic non-linear relationship between SQ and EoU would provide a more accurate result than a linear and other non-linear relationship since higher R^2_{adj} and lower SEE, and a slight difference R^2 values indicate a better function. So, ***H3$_{SQ}$*** is supported. Also, the obtained value for R^2 of the quadratic model is 0.167 (Table 4.11), which concludes that the size of a correlation had a "medium" effect.

The selected quadratic regression function is:

$$EoU = 5.484 + (-1.354 * SQ) + (.246 * SQ^2) \quad (4.9)$$

Table 4.11 Model statistics and parameter estimates of the fitted models (SQ→EoU)

Model	Model Statistics			Parameter Estimates			
	R^2	R^2 (adj)	SEE	b0	b1	b2	b3
Linear	.095	.086	.755	2.811	.315		
Logarithmic	.066	.057	.767	2.910	.827		
Inverse	.042	.033	.777	4.498	-1.864		
Quadratic	.167	.151	.728	5.484	-1.354	.246	
Cubic	.168	.142	.732	4.988	-.856	.091	.015
Compound	.082	.073	.222	2.826	1.090		
Power	.058	.049	.225	2.902	.226		
S	.037	.027	.228	1.500	-.510		
Growth	.082	.073	.222	1.039	.086		
Exponential	.082	.073	.222	2.826	.086		
Logistic	.082	.073	.222	.354	.918		

4.4.1.6 Learner-interface interactivity and TAM main factors (U and EoU) relationships

The result of estimating the effect of learner-interface interactivity on perceived usefulness shows that linear and non-linear correlations were proven. For linear regression, R^2 is equal to 0.133, R^2_{adj} is equal to 0.125, and SEE is equal to 0.994 (β=0.365, F=15.519, p<0.05); and for non-linear regression R^2 is equal 0.187, R^2_{adj} is equal to 0.179, and SEE is equal to 0.359 for S-curve (F=23.274, p<0.05). Accordingly, the S-curve non-linear relationship between LInt and U would provide a more accurate result than a linear and other non-linear relationship since higher R^2 and R^2_{adj} and lower SEE values indicate a better function. So, $\boldsymbol{H4_{LInt}}$ is supported. Also, the obtained value for R^2 of the S-curve model is 0.187 (Table 4.12), which concludes that the size of a correlation had a "medium" effect.

The selected S-curve regression function is:

$$U = e^{1.832+(-2.517/LInt)} \text{ or } \ln U = 1.832 + (-2.517/LInt) \tag{4.10}$$

Table 4.12 Model statistics and parameter estimates of the fitted models (LInt→U)

Model	**Model Statistics**			**Parameter Estimates**			
	R^2	R^2 (adj)	SEE	b0	b1	b2	b3
Linear	.133	.125	.994	1.072	.598		
Logarithmic	.148	.140	.985	.578	2.106		
Inverse	.147	.139	.985	5.012	-5.975		
Quadratic	.151	.134	.988	-1.183	1.877	-.174	
Cubic	.151	.125	.993	-2.164	2.892	-.491	.031
Compound	.145	.137	.369	1.279	1.263		
Power	.174	.166	.362	1.010	.854		
S	.187	.179	.359	1.832	-2.517		
Growth	.145	.137	.369	.246	.234		
Exponential	.145	.137	.369	1.279	.234		
Logistic	.145	.137	.369	.782	.792		

The effect of learner-interface interactivity on perceived ease of use shows that linear and non-linear correlations were proven. For linear regression, R^2 is equal to 0.154, R^2_{adj} is equal to 0.146, and SEE is equal to 0.730 (β=0.393, F=18.444, p<0.05); and for non-linear regression R^2 is equal 0.185, R^2_{adj} is equal to 0.161, and SEE is equal to 0.724 for cubic curve (F=7.515, p<0.05). Accordingly, the cubic non-linear relationship between LInt and EoU would provide a more accurate result than a linear and other non-linear relationship since higher R^2 and R^2_{adj}, and lower SEE values indicate a better function.

So, ***H5**$_{LInt}$* is supported. Also, the obtained value for R^2 of the cubic model is 0.185 (Table 4.13), which concludes that the size of a correlation had a "medium" effect.

The selected cubic regression function is:

$$EoU = 7.718 + (-5.501 * LInt) + (1.891 * LInt^2) + (-1.86 * LInt^3) \quad (4.11)$$

Table 4.13 Model statistics and parameter estimates of the fitted models (LInt→EoU)

Model	Model Statistics			Parameter Estimates			
	R^2	R^2 (adj)	SEE	b0	b1	b2	b3
Linear	.154	.146	.730	2.050	.479		
Logarithmic	.142	.133	.735	1.862	1.534		
Inverse	.103	.094	.752	4.925	-3.718		
Quadratic	.155	.138	.733	1.800	.621	-.019	
Cubic	.185	.161	.724	7.718	-5.501	1.891	-.186
Compound	.173	.164	.211	2.143	1.160		
Power	.167	.159	.212	1.988	.487		
S	.129	.120	.217	1.669	-1.216		
Growth	.173	164	.211	.762	.148		
Exponential	.173	164	.211	2.143	.148		
Logistic	.173	164	.211	.467	.862		

4.4.1.7 Navigation results and TAM main factors (U and EoU) relationships

The result of estimating the effect of navigation on perceived usefulness shows that linear and non-linear correlations were proven. For linear regression, R^2 is equal to 0.192, R^2_{adj} is equal to 0.184, and SEE is equal to 0.959 (β=0.438, F=24.019, p<0.05); and for non-linear regression R^2 is equal 0.216, R^2_{adj} is equal to 0.209, and SEE is equal to 0.353 for S-curve (F=27.899, p<0.05). Accordingly, the S-curve non-linear relationship between Nav and U would provide a more accurate result than a linear and other non-linear relationship since higher R^2 and R^2_{adj} and lower SEE values indicate a better function. So, ***H4**$_{Nav}$* is supported. Also, the obtained value for R^2 of the S-curve model is 0.216 (

Table **4.14**), which concludes that the size of a correlation had a "medium" effect.

The selected S-curve regression function is:

$$U = e^{2.069+(-3.444/Nav)} \text{ or } \ln U = 2.069 + (-3.444/Nav) \quad (4.12)$$

Table 4.14 Model statistics and parameter estimates of the fitted models (Nav→U)

Model	Model Statistics			Parameter Estimates			
	R^2	R^2 (adj)	SEE	b0	b1	b2	b3
Linear	.192	.184	.959	.690	.694		
Logarithmic	.201	.193	.954	-.102	2.601		
Inverse	.204	.196	.952	5.774	-8.945		
Quadratic	.196	.180	.961	-.851	1.520	-.107	
Cubic	.196	.180	.961	-.851	1.520	-.107	.000
Compound	.175	.167	.362	1.210	1.280		
Power	.197	.189	.357	.870	.962		
S	.216	.209	.353	2.069	-3.444		
Growth	.175	.167	.362	.190	.247		
Exponential	.175	.167	.362	1.210	.247		
Logistic	.175	.167	.362	.827	.781		

The effect of navigation on perceived ease of use shows that linear and non-linear correlations were proven. For linear regression, R^2 is equal to 0.264, R^2_{adj} is equal to 0.256, and SEE is equal to 0.681 (β=0.513, F=36.154, p<0.05); and for non-linear regression R^2 is equal 0.266, R^2_{adj} is equal to 0.251, and SEE is equal to 0.683 for cubic curve (F=18.123, p<0.05). Accordingly, the linear relationship between Nav and EoU would provide a more accurate result than a non-linear relationship since higher R^2_{adj}, lower SEE, and slight difference R^2 values indicate a better function. So, ***H5***$\boldsymbol{_{Nav}}$ is not supported. Also, the obtained value for R^2 of the linear model is 0.264 (Table 4.15), which concludes that the size of a correlation had a "large" effect.

The selected linear regression function is:

$$EoU = 1.550 + (.604 * Nav) \tag{4.13}$$

Table 4.15 Model statistics and parameter estimates of the fitted models (Nav→EoU)

Model	Model Statistics			Parameter Estimates			
	R^2	R^2 (adj)	SEE	b0	b1	b2	b3
Linear	.264	.256	.681	1.550	.604		
Logarithmic	.250	.243	.687	1.003	2.161		
Inverse	.222	.214	.700	5.758	-6.943		
Quadratic	.265	.250	.684	2.203	.254	.045	
Cubic	.266	.251	.683	8.138	-5.042	1.550	-.137
Compound	.256	.248	.200	1.931	1.190		
Power	.251	.244	.201	1.626	.634		
S	.232	.225	.203	1.891	-2.078		
Growth	.256	.248	.200	.658	.174		
Exponential	.256	.248	.200	1.931	.174		
Logistic	.256	.248	.200	.518	.840		

4.4.1.8 Course evaluation's system and TAM main factors (U and EoU) relationships

The result of estimating the effect of course evaluation's system on perceived usefulness shows that linear and non-linear correlations were proven. For linear regression, R^2 is equal to 0.248, R^2_{adj} is equal to 0.241, and SEE is equal to 0.925 (β=0.498, F=33.339, p<0.05); and for non-linear regression R^2 is equal 0.259 and 0.250, R^2_{adj} is equal to 0.236 and 0.243, and SEE is equal to 0.928 and .924 for cubic curve (F=11.517, p<0.05) and for logarithmic curve (F=33.729, p<0.05), respectively. Accordingly, the logarithmic non-linear relationship between CES and U would provide a more accurate result than a linear and other non-linear relationship since higher R^2_{adj}, lower SEE, and slight difference R^2 values indicate a better function. So, ***H4***$_{CES}$ is supported. Also, the obtained value for R^2 of the logarithmic model is 0.250 (Table 4.16), which concludes that the size of a correlation had a "large" effect.

The selected logarithmic regression function is:

$$U = .912 + (1.967 * \ln CES) \tag{4.14}$$

Table 4.16 Model statistics and parameter estimates of the fitted models (CES→U)

Model	Model Statistics			Parameter Estimates			
	R^2	R^2 (adj)	SEE	b0	b1	b2	b3
Linear	.248	.241	.925	1.139	.616		
Logarithmic	.250	.243	.924	.912	1.967		
Inverse	.222	.214	.941	4.838	-4.837		
Quadratic	.250	.235	.929	.624	.929	-.044	
Cubic	.259	.236	.928	-1.863	3.571	-.896	.085
Compound	.231	.224	.350	1.406	1.249		
Power	.254	.246	.345	1.246	.740		
S	.249	.241	.346	1.723	-1.914		
Growth	.231	.224	.350	.341	.222		
Exponential	.231	.224	.350	1.406	.222		
Logistic	.231	.224	.350	.711	.801		

The effect of course evaluation's system on perceived ease of use shows that linear and non-linear correlations were proven. For linear regression, R^2 is equal to 0.185, R^2_{adj} is equal to 0.177, and SEE is equal to 0.716 (β=0.431, F=23.001, p<0.05); and for non-linear regression R^2 is equal 0.315, R^2_{adj} is equal to 0.295, and SEE is equal to 0.663 for cubic curve (F=15.198, p<0.05). Accordingly, the cubic non-linear relationship between

CES and EoU would provide a more accurate result than a linear and other non-linear relationship since higher R^2 and R^2_{adj} and lower SEE values indicate a better function. So, ***H5$_{CES}$*** is supported. Also, the obtained value for R^2 of the cubic model is 0.315 (Table 4.17), which concludes that the size of a correlation had a "large" effect.

The selected cubic regression function is:

$$EoU = -.713 + (3.663 * CES) + (-1.064 * CES^2) + (.110 * CES^3) \quad (4.15)$$

Table 4.17 Model statistics and parameter estimates of the fitted models (CES→EoU)

Model	Model Statistics			Parameter Estimates			
	R^2	R^2 (adj)	SEE	b0	b1	b2	b3
Linear	.287	.280	.670	2.105	.493		
Logarithmic	.276	.269	.675	1.971	1.537		
Inverse	.240	.232	.692	5.027	-3.739		
Quadratic	.289	.275	.673	2.492	.258	.033	
Cubic	.315	.295	.663	-.713	3.663	-1.064	.110
Compound	.294	.287	.195	2.234	1.157		
Power	.308	.301	.193	2.093	.475		
S	.296	.289	.195	1.700	-1.216		
Growth	.294	.287	.195	.804	.146		
Exponential	.294	.287	.195	2.234	.146		
Logistic	.294	.287	.195	.448	.864		

4.4.1.9 Course structure and content and TAM main factors (U and EoU) relationships

The result of estimating the effect of course structure and content on perceived usefulness shows that linear and non-linear correlations were proven. For linear regression, R^2 is equal to 0.175, R^2_{adj} is equal to 0.167, and SEE is equal to 0.969 (β=0.418, F=21.416, p<0.05); and for non-linear regression R^2 is equal 0.215, R^2_{adj} is equal to 0.207, and SEE is equal to 0.353 for S-curve (F=27.698, p<0.05). Accordingly, the S-curve non-linear relationship between CSC and U would provide a more accurate result than a linear and other non-linear relationship since higher R^2 and R^2_{adj} and lower SEE values indicate a better function. So, ***H4$_{CSC}$*** is supported. Also, the obtained value for R^2 of the S-curve model is 0.215 (Table 4.18), which concludes that the size of a correlation had a "medium" effect.

The selected S-curve regression function is:

$$U = e^{2.056+(-3.441/CSC)} \text{ or } \ln U = 2.056 + (-3.441/CSC) \quad (4.16)$$

Table 4.18 Model statistics and parameter estimates of the fitted models (CSC→U)

Model	Model Statistics			Parameter Estimates			
	R^2	R^2 (adj)	SEE	b0	b1	b2	b3
Linear	.175	.167	.969	.863	.641		
Logarithmic	.191	.183	.960	.020	2.486		
Inverse	.204	.196	.952	5.748	-8.964		
Quadratic	.197	.181	.961	-2.800	2.598	-.253	
Cubic	.197	.181	.961	-2.800	2.598	-.253	.000
Compound	.163	.155	.365	1.272	1.260		
Power	.190	.182	.359	.902	.926		
S	.215	.207	.353	2.056	-3.441		
Growth	.163	.155	.365	.240	.231		
Exponential	.163	.155	.365	1.272	.231		
Logistic	.163	.155	.365	.786	.794		

The effect of course structure and content on perceived ease of use shows that linear and non-linear correlations were proven. For linear regression, R^2 is equal to 0.242, R^2_{adj} is equal to 0.235, and SEE is equal to 0.691 (β=0.492, F=32.314, p<0.05); and for non-linear regression R^2 is equal 0.270, R^2_{adj} is equal to 0.255, and SEE is equal to 0.682 for cubic curve (F=18.470, p<0.05). Accordingly, the quadratic non-linear relationship between CSC and EoU would provide a more accurate result than a linear and other non-linear relationship since higher R^2 and R^2_{adj} and lower SEE values indicate a better function. So, ***H5*$_{CSC}$** is supported. Also, the obtained value for R^2 of the quadratic model is 0.270 (Table 4.19), which concludes that the size of a correlation had a "large" effect.

The selected quadratic regression function is:

$$EoU = 4.723 + (-1.060 * CSC) + (.209 * CSC^2) \quad (4.17)$$

Table 4.19 Model statistics and parameter estimates of the fitted models (CSC→EoU)

Model	Model Statistics			Parameter Estimates			
	R^2	R^2 (adj)	SEE	b0	b1	b2	b3
Linear	.242	.235	.691	1.689	.561		
Logarithmic	.217	.209	.702	1.237	1.970		
Inverse	.182	.174	.718	5.569	-6.300		
Quadratic	.270	.255	.682	4.723	-1.060	.209	
Cubic	.269	.255	.682	5.662	-1.873	.435	-.020
Compound	.215	.207	.206	2.070	1.167		
Power	.195	.187	.208	1.818	.546		
S	.165	.157	.212	1.801	-1.755		
Growth	.215	.207	.206	.728	.154		
Exponential	.215	.207	.206	2.070	.154		
Logistic	.215	.207	.206	.483	.857		

4.4.1.10 HCI main factors and (course grades or GPAs) relationships

When conducting the linear test, it was found that there was no relationship between the HCI main factors with students' outcomes. When testing the non-linearity, it was found that there was a relationship between the LInt and students' GPAs or their grades in the course.

The result of estimating the effect of learner-interface interactivity on GPAs shows that non-linear correlations were proven, while linear correlation were not proven (p>0.05). For non-linear regression R^2 is equal 0.071, R^2_{adj} is equal to 0.062, and SEE is equal to 0.406 for S-curve (F=7.693, p<0.05). Accordingly, the S-curve non-linear relationship between LInt and GPAs would provide a more accurate result than other non-linear relationship since higher R^2 and R^2_{adj} and lower SEE values indicate a better function. So, ***H8**$_{LInt, GPA}$* is supported. Also, the obtained value for R^2 of the S-curve model is 0.071 (Table 4.20), which concludes that the size of a correlation had a "small" effect.

The selected S-curve regression function is:

$$GPA = e^{1.393+(-1.634/LInt)} \text{ or } \ln GPA = 1.393 + (-1.634/LInt) \qquad (4.18)$$

Table 4.20 Model statistics and parameter estimates of the fitted models (LInt→GPA)

Model	Model Statistics				Parameter Estimates			
	R^2	R^2 (adj)	SEE	Sig.	b0	b1	b2	b3
Linear	0.018	0.009	1.096	0.174	1.934	0.229		
Logarithmic	0.027	0.018	1.091	0.094	1.565	0.940		
Inverse	0.036	0.026	1.086	0.056	3.643	-3.049		
Quadratic	0.045	0.026	1.086	0.098	-0.982	1.883	-0.225	
Cubic	0.048	0.019	1.090	0.183	1.207	-0.382	0.481	-0.069
Compound	0.040	0.030	0.413	0.044	1.574	1.137		
Power	0.056	0.047	0.409	0.016	1.305	0.513		
S	0.071	0.062	0.406	0.007	1.393	-1.634		
Growth	0.040	0.030	0.413	0.044	0.454	0.129		
Exponential	0.040	0.030	0.413	0.044	1.574	0.129		
Logistic	0.040	0.030	0.413	0.044	0.635	0.879		

The result of estimating the effect of learner-interface interactivity on course grades shows that non-linear correlations were proven, while linear correlation were not proven (p>0.05). For non-linear regression R^2 is equal 0.158, R^2_{adj} is equal to 0.146, and SEE is equal to 1.793 for cubic curve (F=6.187, p<0.05). Accordingly, the cubic curve non-linear relationship between LInt and course grades would provide a more accurate result than other non-linear relationship since higher R^2 and R^2_{adj} and lower SEE values indicate a better function. So, ***H8****LInt, Grades* is supported. Also, the obtained value for R^2 of the cubic curve model is 0.158 (Table 4.21), which concludes that the size of a correlation had a "medium" effect.

The selected cubic regression function is:

$$Grades = 69.043 + (-48.674 * LInt) + (21.713 * LInt^2) + (-2.367 * LInt^3) \quad (4.19)$$

Table 4.21 Model statistics and parameter estimates of the fitted models (LInt→Grades)

Model	Model Statistics				Parameter Estimates			
	R^2	R^2 (adj)	SEE	Sig.	b0	b1	b2	b3
Linear	0.048	0.036	16.850	0.054	27.207	10.230		
Logarithmic	0.145	0.137	16.752	0.000	19.584	35.401		
Inverse	0.139	0.131	16.808	0.000	93.625	-98.619		
Quadratic	0.148	0.131	16.803	0.000	-6.217	29.175	-2.584	
Cubic	0.158	0.146	16.793	0.001	69.043	-48.674	21.713	-2.367
Compound	0.138	0.129	0.338	0.000	28.263	1.231		
Power	0.153	0.145	0.335	0.000	23.798	0.731		
S	0.154	0.146	0.335	0.000	4.712	-2.087		
Growth	0.138	0.129	0.338	0.000	3.342	0.208		
Exponential	0.138	0.129	0.338	0.000	28.263	0.208		
Logistic	0.138	0.129	0.338	0.000	0.035	0.812		

4.4.1.11 TAM main factors and (course grades or GPAs) relationships

When conducting the linear test, it was found that there was no relationship between the TAM main factors with students' outcomes. When testing the non-linearity, it was found that there was a relationship between the U and students' grades in the course.

The result of estimating the effect of usefulness on course grades shows that non-linear correlations were proven, while linear correlation were not proven (p>0.05). For non-linear regression R^2 is equal 0.085, R^2_{adj} is equal to 0.057, and SEE is equal to 17.505 for cubic curve (F=3.064, p<0.05). Accordingly, the cubic curve non-linear relationship between U and course grades would provide a more accurate result than other non-linear relationship since higher R^2 and R^2_{adj} and lower SEE values indicate a better function. So,

***H9**$_{U, Grades}$* is supported. Also, the obtained value for R^2 of the cubic curve model is 0.085 (Table 4.22), which concludes that the size of a correlation had a "small" effect.

The selected cubic regression function is:

$$Grades = 6.352 + (56.169 * U) + (-15.228 * U^2) + (1.270 * U^3) \quad (4.20)$$

Table 4.22 Model statistics and parameter estimates of the fitted models (U→Grades)

Model	Model Statistics				Parameter Estimates			
	R^2	R^2 (adj)	SEE	Sig.	b0	b1	b2	b3
Linear	0.011	0.001	18.016	0.289	61.621	1.792		
Logarithmic	0.028	0.019	17.860	0.090	58.840	7.636		
Inverse	0.050	0.041	17.656	0.023	75.218	-21.809		
Quadratic	0.074	0.056	17.517	0.021	32.943	22.735	-3.348	
Cubic	0.085	0.057	17.505	0.032	6.352	56.169	-15.228	1.270
Compound	0.027	0.017	0.359	0.099	53.154	1.057		
Power	0.048	0.038	0.355	0.027	50.994	0.200		
S	0.069	0.060	0.352	0.007	4.340	-0.513		
Growth	0.027	0.017	0.359	0.099	3.973	0.056		
Exponential	0.027	0.017	0.359	0.099	53.154	0.056		
Logistic	0.027	0.017	0.359	0.099	0.019	0.946		

As a summary, the supported hypotheses were derived from the non-linearity of integration of HCI factors with perceived EoU and U, and were proven to be significant determinants, as shown in Table 4.23 where perceived CES is the strongest determinant in the model.

4.4.2 Moderation results

Referring to the analysis in the first part of this study, we will find that gender moderate only the relationship between VD and EOU; and between CE and EoU. Also, it indicates that the effect of VD or CE on EOU is stronger for males. So, the ***H6**$_{gender}$* is partially supported. Furthermore. Besides, using SMART phones to connect to Khas Learn moderates only the relationship between CQ and EoU, and between CE and EoU. It indicates that the effect of CQ on the EoU is stronger for SMART phone usage, while the effect of CE on the EoU is stronger for not using a desktop. So, the ***H7**$_{SMART}$* and ***H7**$_{Desktop}$* are partially supported. Moreover, the daily time student spends on the internet studying moderate only the relationship between CQ and U. It indicates that the effect of CQ on the U is stronger for 1-3 hr. daily using the internet, while it is stronger for 1-2 hr. weekly online studying. So, the ***H7**_{Time}* is partially supported.

Table 4.23 Hypothesis Testing Results (Linear and Non-Linear Regression Tests)

Hypotheses	Regression	Regression Type	R^2	Size of Effect	β	p-Value	Support H
H1	EoU → U	Cubic	.273	Large	.522	.000	Yes
H2	VD → U	Quadratic	.109	Medium	.330	.003	Yes
	CE → U	Cubic or Quadratic	.199	Medium	.446	.000	Yes
	CQ → U	Linear	.115	Medium	.339	.000	No
	SQ → U	Quadratic	.267	Large	.517	.000	Yes
H3	VD → EoU	Cubic	.076	Small	.276	.049	Yes
	CE → EoU	Cubic	.187	Medium	.432	.000	Yes
	CQ → EoU	Linear	.166	Medium	.407	.000	No
	SQ → EoU	Quadratic	.167	Medium	.409	.000	Yes
H4	LInt → U	S-curve	.187	Medium	.432	.000	Yes
	Nav → U	S-curve	.216	Medium	.465	.000	Yes
	CES → U	Logarithmic	.250	Large	.500	.000	Yes
	CSC → U	S-curve	.215	Medium	.464	.000	Yes
H5	LInt → EoU	Cubic	.185	Medium	.430	.000	Yes
	Nav → EoU	Linear	.264	Large	.514	.000	No
	CES → EoU	Cubic	.315	Large	.561	.000	Yes
	CSC → EoU	Quadratic	.185	Medium	.430	.000	Yes
H8	LInt → GPA	S-curve	.071	Small	.266	.007	Partially
	LInt → Grade	Cubic	.158	Medium	.397	.001	Partially
H9	U → GPA	Cubic	.085	Small	.292	.032	Partially

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

Also, means include gender, SMART phone usage, and time spent on the internet or studying as moderators would increase the explanatory power of the model.

4.4.3 Conceptual model testing results

Based on the results of all hypotheses, the researcher introduced a conceptual model as a framework for the non-linear relationship between HCI factors and EoU and U (Figure 4.2).

4.5 Discussion

This study demonstrates the role of interactive learning in the success of e-learning, which is consistent with the study outputs of Cidral et al. (2018). Furthermore, the path coefficient size of the relationships regarding perceived usefulness, according to the results, ranged between 0.330 and 0.522 were for all ($\beta_{avg.}$ = 0.446) while regarding perceived ease of use ranges between 0.276 and 0.561 were for all ($\beta_{avg.}$ = 0.432). This means that the model presented in this study showed a higher effect size of the predictors compared to Abdullah and Ward (2016) study, which showed the rate of this effect in several studies during the past ten years. Therefore, this study, after using the nonlinear analysis, contributed to better predicting the level of the effect size rates of the independent factors related to interaction and interactivity, in their impact on the dependent factors, and not only on the factors of users' characteristics but also the ones that enhance the acceptance.

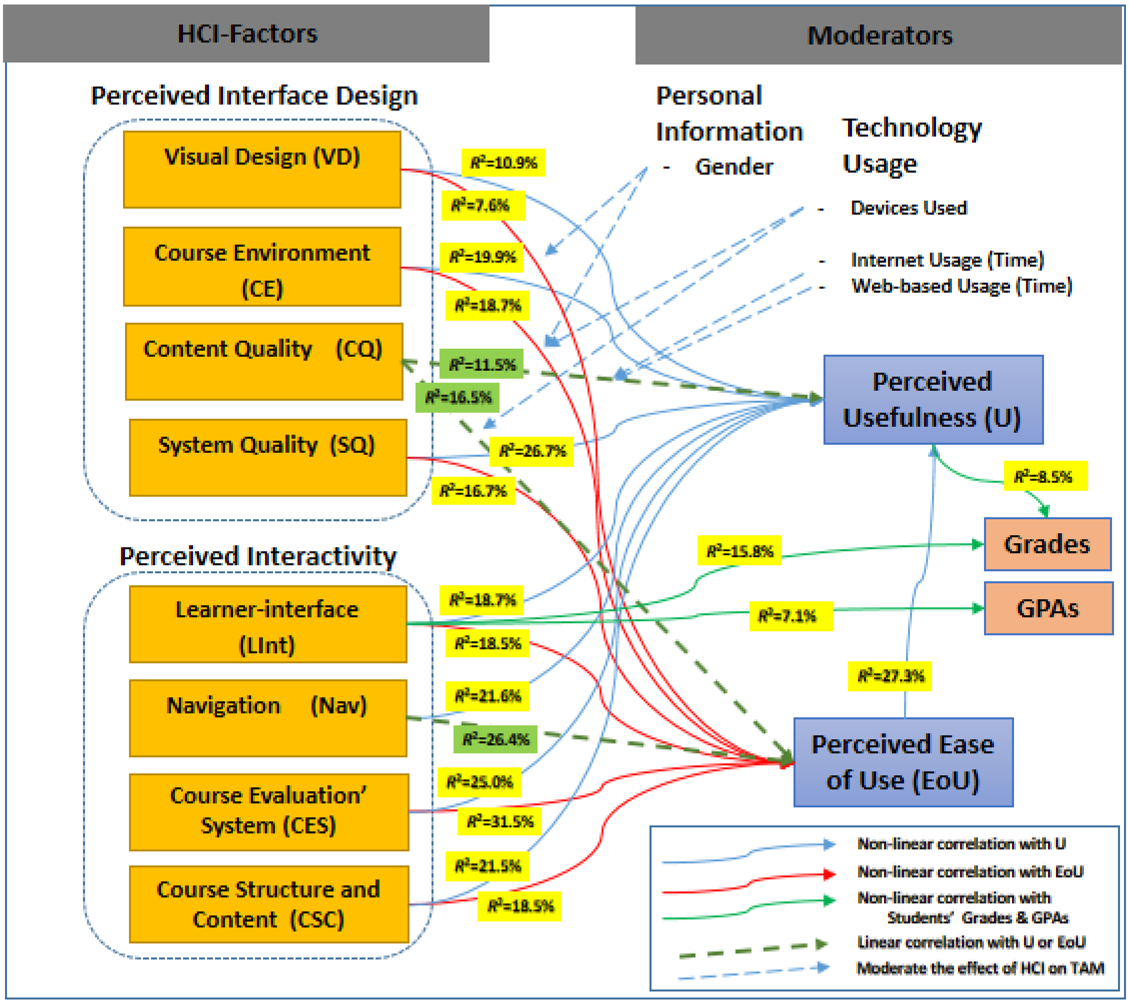

Figure 4.2 The researcher's conceptual model

4.5.1 Non-linearity

For a complete explanation of the nonlinearity compared with linear relationships, the graphic presentations (figures 4.3-4.10) are useful to figure out the pattern of changes in the resulting attribute, based on changes in the outcomes' values. They are calculated after substitution in modelled equations with threshold values that are associated with predictors, and multiplied by coefficients in each case. As shown in the graphics, most of the nonlinear relationships between the factors appeared in the form of a U-shaped curve or inverted U-shaped curve that's consistent with Hakami (2018) clue.

Figure 4.3 presents the scatter plot of linear and cubic relations in the regression models for the factors EoU and U. On the left part, the curve of non-linearity is oriented as a positive trend paralleled with linearity from the lower left quadrant toward the upper right quadrant. There is a slight difference between the results of linearity and nonlinearity in determining the level of students' perception of EoU and the extent to which it affects the perception of improvement in learning performance, efficiency and productivity when incremented by a specified value. Attention to EoU increases effectiveness and impact, at a slightly better rate, on the category of students who disagree or are neutral with the easiest of getting the information from Khas Learn, comprehending provided information by the system, or with no trouble in using Khas Learn in performing tasks. Furthermore, the path coefficient size for the two models (β_{linear}=0.492, $\beta_{\text{nonlinear}}$=0.522), which is slightly higher than the average ($\beta_{\text{avg.}}$ =0.400), according to the study of Šumak et al. (2011).

a)

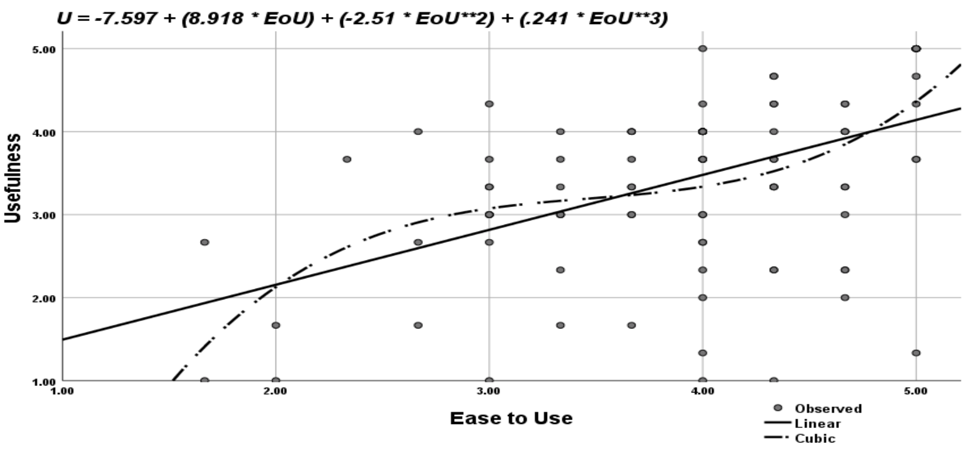

Figure 4.3 Linear and non-linear correlation model for the variables: EoU and U, (a) linear and cubic relations EoU, U.

Figure 4.4a presents the scatter plot of linear and quadratic relations in the regression models for the factors VD and U. On the left part, the curve of non-linearity is oriented neutrally and paralleled with the abscission while there is a positive trend paralleled with linearity from the middle toward the upper right quadrant. The gap is obvious between the two models considering the enhancement in the students' perceptions who disagree or strongly disagree with the readability and consistency of Khas Learn's text, colors, and layout, and the attractiveness of the system design. This indicates that this group of students may not be affected by any effort in improving VD as a prerequisite to improving their perception of U. This was not answered by linearity.

Figure 4.4b presents the scatter plot of linear and cubic relations in the regression models for the factors VD and EoU. On the left part, the curve of non-linearity is oriented negatively. The gap widens between the two models, since the higher the student's perceived VD who moved from strongly disagree to neutrality, the lower their perceived of EoU in the nonlinear correlation: and this contrasts with the linear relationship. Then, this trend takes a positive escalation in convictions in parallel with the linear relationship to become differences of low significance. However, even if the convictions of the same group of students whose initial impressions were poor about the attractiveness of the interface design and consistency of the layout are improved to a positive impression, the increase in the perception of ease of use will remain below the required level and less than before.

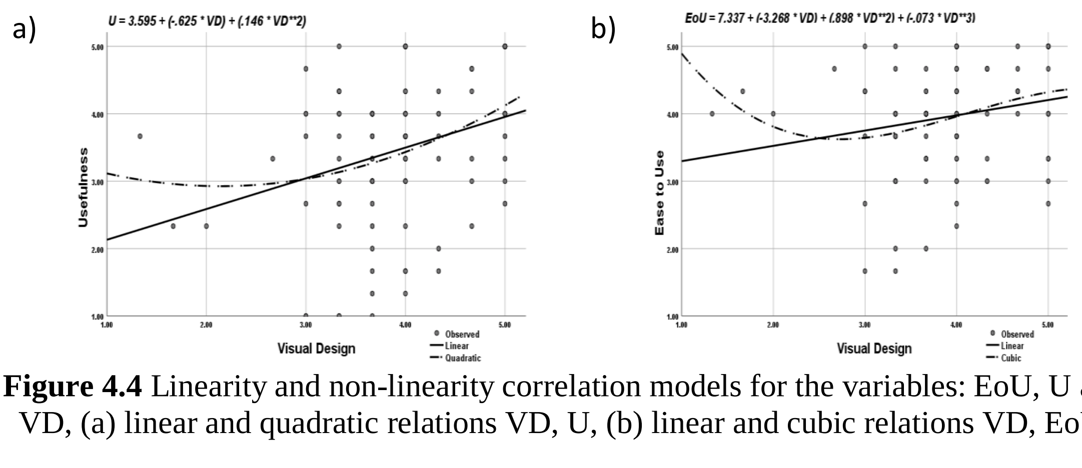

Figure 4.4 Linearity and non-linearity correlation models for the variables: EoU, U and VD, (a) linear and quadratic relations VD, U, (b) linear and cubic relations VD, EoU.

Figure 4.5a presents the scatter plot of linear and cubic relations for the factors CE and U. On the left part, the curve of non-linearity is oriented to a positive trend paralleled with linearity from the lower left quadrant toward the upper right quadrant. There is a slight difference between the results of linearity and nonlinearity in determining the level of students' perception of CE and the extent to which it affects the perception of improvement in learning performance, efficiency and productivity when incremented by a specified value. It is thus similar to the shape of the linear and nonlinear relationship between EoU and U.

Figure 4.5b presents the scatter plot of linear and cubic relations in the regression models for the factors CE and EoU. On the left part, the curve of non-linearity is oriented negatively. The gap widens between the two models, since the higher the student's perceived CE who moved from strongly disagree to neutrality, the lower is their perceived of EoU in the nonlinear correlation: and this contrasts with the linear relationship. Then, this trend takes a positive escalation in convictions in parallel with the linear relationship to become differences of low significance. However, even if the convictions of the same group of students whose initial impressions were poor about the extent of the course webpage were presented through the (Khas Learn), it enables the student to actively learn, share ideas, engage in critical thinking, and self-directed work with the possibility of receiving feedback regardless of time and place, so they are improved to a positive impression. The increase in the perception of ease of use will remain below the required level and less than before although it gives better results than linearity in students who agree about their perception of CE.

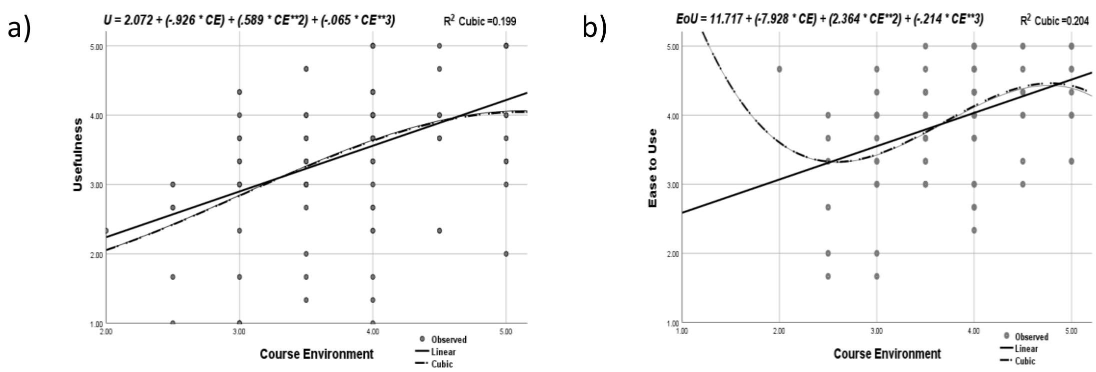

Figure 4.5 Linearity and non-linearity correlation models for the variables: EoU, U and CE, (a) linear and cubic relations CE, U, (b) linear and cubic relations CE, EoU.

Figure 4.6a presents the scatter plot of linear and quadratic relations in the regression models for the factors SQ and U. On the left part, the curve of non-linearity is oriented neutrally and paralleled with the abscision while there is a positive trend paralleled with linearity from the middle toward the upper right quadrant. The gap is obvious between the two models considering the enhancement in the students' perceptions who disagree or strongly disagree with the Khas Learn being fun to operate, satisfactory in its functions, or its course materials to be accessible without much effort. This indicates that this group of students who are not satisfied with the system quality may not be affected by any effort in improving SQ as a prerequisite to improving their perception of U. This was not answered by linearity. Furthermore, these results are similar to the previous conclusions related to the quadratic nonlinearity between VD and U. Furthermore, the path coefficient size for the two models (β_{linear}=0.496, $\beta_{nonlinear}$=0.517), which is higher than the average according to the study of Šumak et al. (2011) where ($\beta_{avg.}$=0.330).

Figure 4.6b presents the linear and quadratic relations in the regression models for the factors SQ and EoU. On the left part, the curve of non-linearity is oriented negatively, and the downward curvature appears sharply at the center, which approaches students who are neutral in their perceptions. The gap widens between the two models since the higher the student's perceived SQ who moved from strongly disagree to neutrality, the lower is their perceived of EoU in the nonlinear correlation: and this contrasts with the linear relationship. Then, this trend takes a positive escalation in convictions in parallel with the linear relationship to become more significant differences. Here, the effect of improving SQ on students' perceived EoU appears, and these results differ in the conclusions of the nonlinear cubic relationship between CE and VD on EoU, concerning students who agree or strongly agree with the functionality and quality of the system. Furthermore, the path coefficient size for the two models (β_{linear}=0.307, $\beta_{nonlinear}$=0.409) in which nonlinearity path coefficient size is higher than the average, according to the study of Šumak et al. (2011) where ($\beta_{avg.}$=0.300).

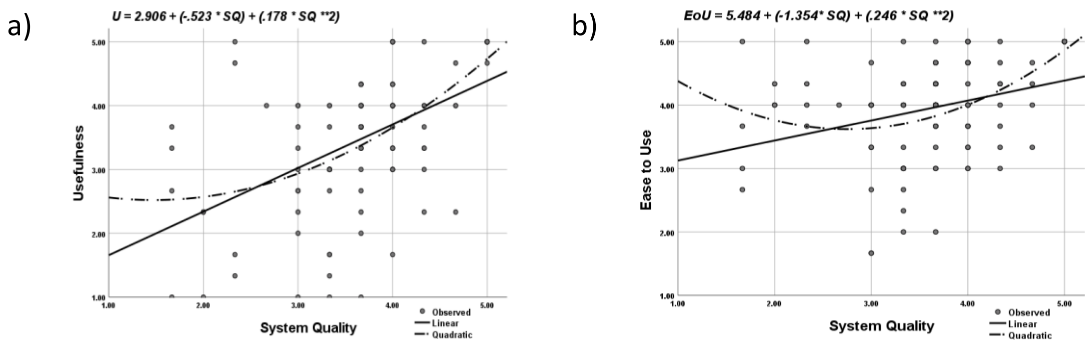

Figure 4.6 Linearity and non-linearity correlation models for the variables: EoU, U and SQ, (a) linear and quadratic relations SQ, U, (b) linear and quadratic relations SQ, EoU.

Figure 4.7a presents the scatter plot of linear and S-curve relations for the factors LInt and U. On the left part, the curve of non-linearity is oriented to a positive trend paralleled with linearity from the lower left quadrant toward the upper right quadrant. There is a slight variance between the results of linearity and nonlinearity outside the center of the coordinate system in determining the level of students' perception of LInt and the extent to which it positively affects the perceived usefulness. Although the variance increases in the sides in favor of the linear relationship, nonlinearity remains the most important interpretation coefficient for the dependent variable. It is thus similar to the shape of the linear and nonlinear relationship between CE and U, but with less variance.

Figure 4.7b presents the linear and cubic relations in the regression models for the factors LInt and EoU. On the left part, the curve of non-linearity is oriented negatively. The variance increases between the two models, since the higher the student's perceived LInt who moved from strongly disagree to neutrality, the lower is their perceived of EoU in the nonlinear correlation: this contrasts with the linear relationship. Then, this trend takes a positive escalation in convictions in parallel with the linear relationship to become differences of low significance. However, even if the convictions of the same group of students whose initial impressions were negative about the extent to which the Khas Learn system helps in mapping and locating their needed information, tracking their status, accessing the online teaching materials anytime, and accomplishing the course tasks more quickly, they are improved to a positive impression. But in contrast with the previous conclusion regarding the nonlinear relationship between CE, VD and EoU, the rate of increase in perceived EoU improves with the development of the independent factor if the student is moved from a low level of perception to a very high level.

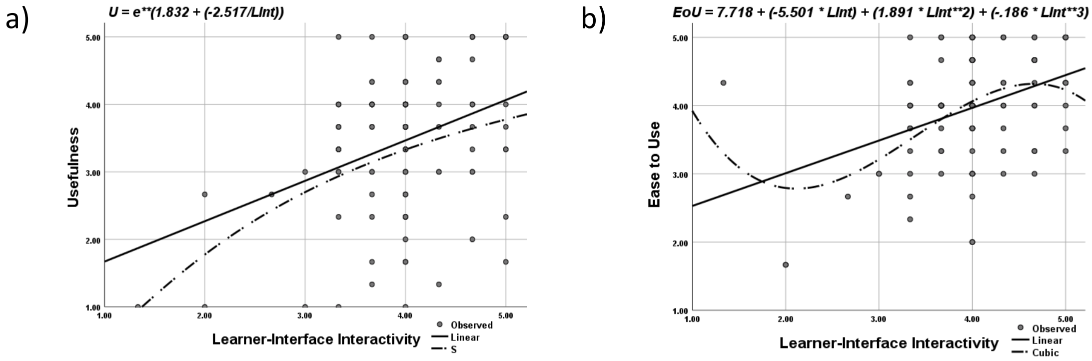

Figure 4.7 Linearity and non-linearity correlation models for the variables: EoU, U and LInt, (a) linear and S-curve relations LInt, U, (b) linear and cubic relations LInt, EoU.

Figure 4.8a presents the scatter plot of linear and S-curve relations for the factors Nav and U. On the left part, the curve of non-linearity is oriented to a positive trend paralleled with linearity from the lower left quadrant toward the upper right quadrant. There is a slight variance between the results of linearity and nonlinearity outside the center of the coordinate system in determining the level of students' perception toward the convenience of the navigational structure of Khas Learn, the ease to find the information that they need, and the satisfaction with the work of system links; and the extent to which it positively affects the perceived usefulness. Although the variance increases in the sides in favor of the linear relationship, nonlinearity remains the most important interpretation coefficient for the dependent variable. It is thus similar to the shape of the linear and nonlinear relationship between LInt and U. **Figure 4.8**b presents the scatter plot of linear relation for the factors Nav and EoU.

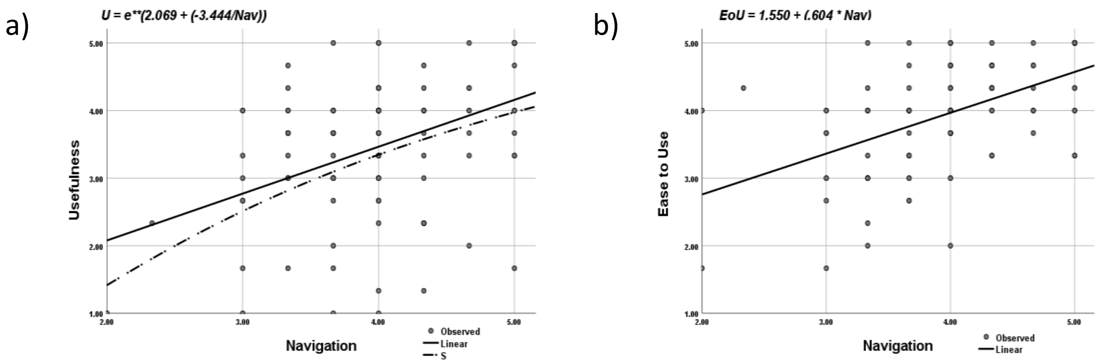

Figure 4.8 Linearity and non-linearity correlation models for the variables: EoU, U and Nav, (a) linear and S-curve relations Nav, U, (b) linear relation Nav, EoU.

Figure 4.9a presents the scatter plot of linear and logarithmic relations for the factors CES and U. On the left part, the curve of non-linearity is oriented to a positive trend paralleled with linearity from the lower left quadrant toward the upper right quadrant. There is a slight variance between the results of linearity and nonlinearity in determining the level of students' perception about the goodness of online self-assessment tools provided by the Khas Learn and the extent to which it affects the perception of improvement in learning performance, efficiency and productivity when incremented by a specified value. It is thus similar to the shape of the linear and nonlinear relationship between CE and U.

Figure 4.9b presents the linear and cubic relations in the regression models for the factors CES and U. On the left part, the curve of non-linearity is oriented to a positive trend paralleled with linearity from the lower left quadrant toward the upper right quadrant. There is a slight variance between the results of linearity and nonlinearity in determining the level of students' perception of EoU and the extent to which it affects the perception of improvement in learning performance, efficiency and productivity when incremented by a specified value. Attention to EoU is increased in effectiveness and impact, at a slightly better rate, on the category of students who disagree or are neutral with the perceived CES. It is thus similar to the shape of the linear and nonlinear relationship between EoU and U.

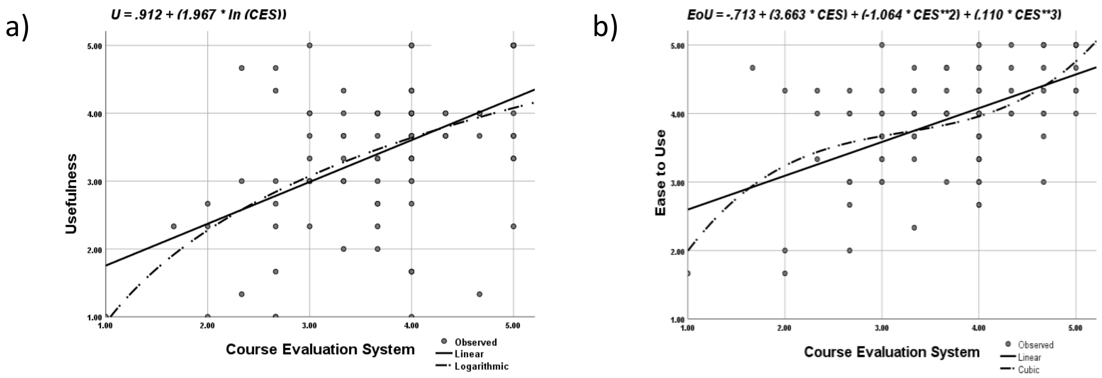

Figure 4.9 Linearity and non-linearity correlation models for the variables: EoU, U and CES, (a) linear and logarithmic relations CES, U, (b) linear cubic relations CES, EoU.

Figure 4.10a presents the scatter plot of linear and S-curve relations for the factors CSC and U. On the left part, the curve of non-linearity is oriented to a positive trend paralleled with linearity from the lower left quadrant toward the upper right quadrant. There is a slight variance between the results of linearity and nonlinearity outside the center of the coordinate system in determining the level of students' perception toward the consistency of the online course content with its objectives, the organization of the online course in a manner that helps to understand the underlying concepts and confidently complete the knowledge or skill presented; and the extent to which it positively affects the perceived usefulness. Although the variance increases in the sides in favor of the linear relationship, nonlinearity remains the most important interpretation coefficient for the dependent variable. It is thus similar to the shape of the linear and nonlinear relationship between Nav and U.

Figure 4.10b presents the linear and quadratic relations in the regression models for the factors CSC and EoU. In the left part, the curve of non-linearity is oriented negatively, and the downward curvature appears sharply at the center, which approaches students who are neutral in their perceptions. The variance widens between the two models since the higher the student's perceived CSC who moved from strongly disagree to neutrality, the lower is their perceived of EoU in the nonlinear correlation: and this contrasts with the linear relationship. Then, this trend takes a positive escalation in convictions in parallel with the linear relationship to become more significant differences, which are similar to the relationship between SQ and EoU. Here, the effect of improving CSC on students' perceived EoU appears, and these results differ in the conclusions of the nonlinear cubic relationship between CE and VD on EoU, concerning students who agree or strongly agree with the consistency of the online course content with its objectives.

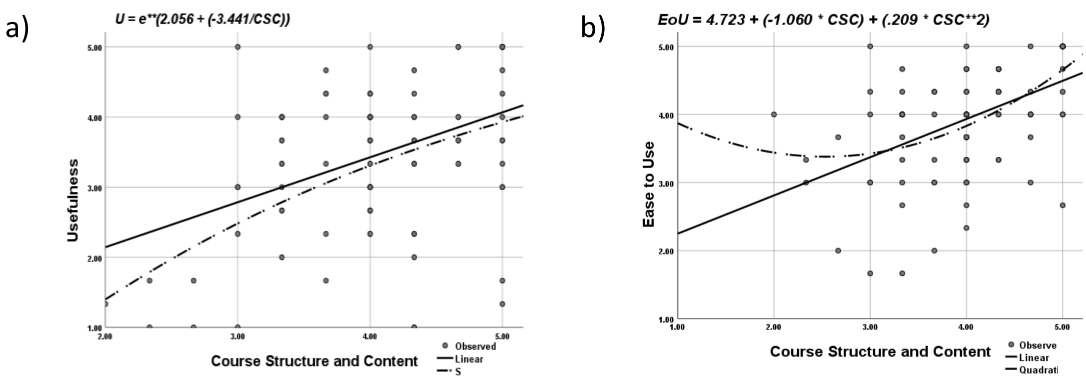

Figure 4.10 Linearity and non-linearity correlation models for the variables: EoU, U and CSC, (a) linear and S-curve relations CSC, U, (b) linear quadratic relations CSC, EoU.

Figure 4.11a presents the scatter plot of S-curve relation for the factors LInt and GPAs. On the left part, the curve of non-linearity is oriented to a positive trend paralleled with linearity from the lower left quadrant toward the upper right quadrant. That implies the improvement in students' perceptions regarding the extent to which the Khas Learn system helps in mapping and locating their needed information, tracking their status, accessing the online teaching materials anytime, and accomplishing the course tasks more quickly; it leads to exponential improvements in students' GPAs, although this relationship was not detected in the linear test.

Figure 4.11b presents the cubic relation in the regression model for the factors LInt and course grades. On the left part, the curve of non-linearity is oriented slightly negative among the group of students who have a negative perception toward LInt, as the improvement in LInt negatively affects the students' grades in the course who earn 40% or less. While this relationship is reversed in the category of students whose grades exceed 40%, so that the development in LInt positively affects the grades of students in the course. Therefore, the rate of increase in students' grades improves with the development of the independent factor if the students are moved from a low level of perceived LInt to a high level, where the S-shape was observed. Also, this relationship was not detected in the linear test.

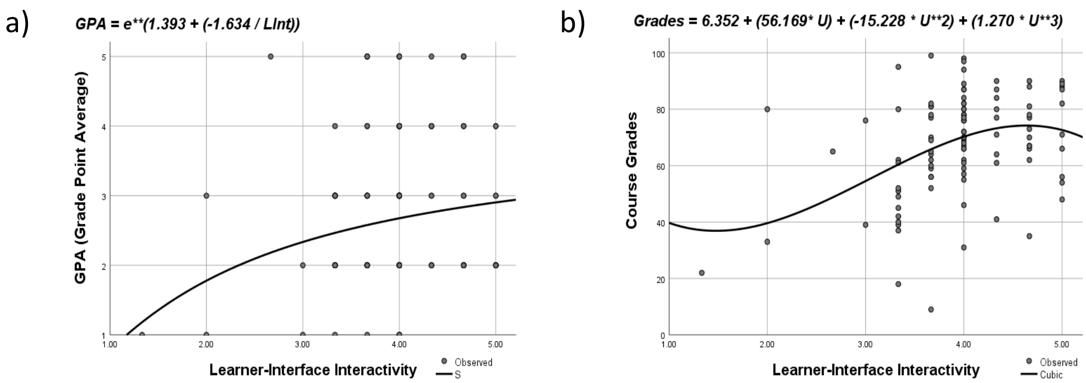

Figure 4.11 Non-linearity correlation models for the variables: GPAs, Grades and LInt, (a) S-curve relations LInt, GPAs, (b) cubic relations LInt, Grades.

Figure 4.12 presents the scatter plot of cubic relation in the regression model for the factors U and students' grades. On the left part, the curve of non-linearity is oriented as a positive trend within the upper left quadrant. Then the curve of non-linearity is reversed and oriented as a negative trend within the upper right quadrant. But, there is a slight difference between the results of nonlinearity in determining the level of students' perception of U and the extent to which it affects the improvement in students' performance. Where the U-shape was observed but is flattened in the middle, shows that the highest level of improvement in perceived usefulness in the group of students who are neutral in their perceptions and will improve their grades. Nevertheless, this improvement keeps their grades within 60% and 70%. Thus, the non-linear assumption provided explanations that the linear assumption did not provide or prove.

a)

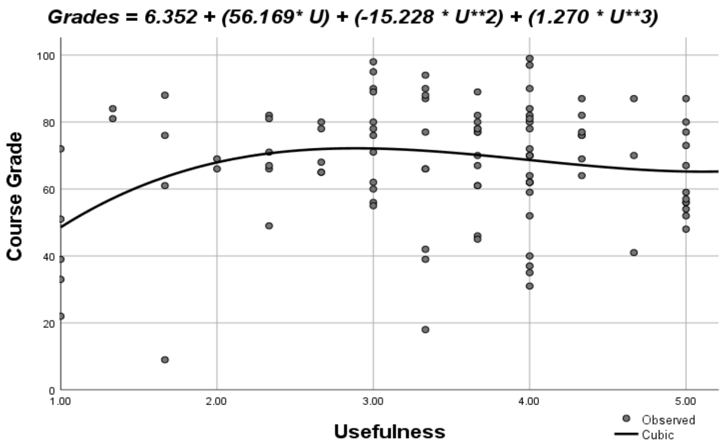

Figure 4.12 Non-linearity correlation models for the variables: U and Grades, (a) cubic relations U, Grades.

When using non-linearity in models, associated with TAM extended by HCI main factors, the magnitudes of β increases up to 25.7%. As does the relationship between VD and EoU, where the rate of increase in all non-linear correlations is around 8.6% over linear correlations. Also the magnitudes of R^2 increases up to 44.7% in non-linearity over linearity, hence it has a finer explanation power than the one followed by the common linear method. This is consistent with the Rondan-Cataluña et al. (2015), who confirmed this improvement in the technology acceptance models while considering non-linear relationships.

According to the results of non-linearity in this study, some relationships reversed the direction of influence from negative to positive or vice versa, depending on the nature of the independent factor at a specific level in the dependent factor. All of these relations were related to the effects of HCI factors on perceived ease of use as VD, CE, SQ, LInt, and CSC; and related to the effects of LInt and U on students' grades in the courses. This is consistent with Kock (2016), who also argues that nonlinearity helps reach the findings that differ from their linear results when reversing the direction of its influence. Furthermore, this helps avoid the incomplete or erroneous explanations caused by the results of linearity interpretations and reduce the underestimating or overstating of the effects resulting from the linearity, according to Titah and Barki (2009).

Moreover, 85% of the relationships in this model, prove to be nonlinear over linear, consistent with Cariou et al. (2014), who concluded the non-linearity in most relationships between factors in social and economic sciences. 76.5% have a U-shape, as the relation between (SQ, LInt, Nav, CES, and CSC) with usefulness; and between (U and LInt) with students' outcomes. Or they have inverted U-shape as the relationships between (VD, CE, SQ, and CSC) with usefulness or ease of use, while 23.5% have an S-shape, as the relationships between (LInt and CES) with ease of use or with students' grades. This is consistent with Rondan-Cataluña et al. (2015), who indicated that most nonlinear links concerning social factors have the form U-shape or inverted U-shape. Also, some relationships have one "turning point" which points to the minimum or maximum value that represents increasing or decreasing around this value. Thus, they achieve the theory of the U-shape, or it has two "turning points" as in the S-shape, and thus they agree with Haans et al. (2016). Consequently, all the results of these graphics are consistent with Salim et al. (2015), who debated that if these results are overlooked, using linear coefficients rather than nonlinear coefficients may prevent potential opportunities for understanding the complex links which exist between the dependent and independent variables in technology acceptance models.

In addition, some constructs have a medium-size effect on the acceptance of technology, but the improvement in these factors (VD, SQ, and LInt) negatively affects the level of perceived ease of use. Thus, the nonlinearity assumption helped capture the more sophisticated integrating effects in behavioural decisions in the context of technology acceptance. This is consistent with what Cook Aloqaily et al. (2019) explored.

Furthermore, in this study, it was discovered that there is a nonlinear effect of LInt as well as the perceived U on students' performance (GPAs and grades in the courses). These effects were not detected in the linear assumption, so this result is consistent with Bervell and Umar (2017), who prove that in some cases related to the acceptance of technology, some constructs are significant in the nonlinear correlation while not significant in the linear regression test.

4.5.2 Gender as a moderator

Since there is evidence that proves the effect of the moderating, the interaction scatters plot was employed to explore what level of user properties this effect lies in. In Figure 4.13a and Figure 4.13b, the male group has a steep linear slope in an increasingly positive direction. The females' group has a steep linear slope in decreasing negative trend, which shows that males have an enhancing effect for perceived ease of use and visual design link in contrast to females. This implies that males are more affected when CE is helpful in active learning, critical thinking development, idea sharing, and contextual learning, and when VD has a consistent layout, readable graphics, attractive design, which makes them perceive their learning via the web to be effortless. These findings are consistent with the past studies (Binyamin et al., 2020; Shaouf & Altaqqi, 2018; Al-Aulamie, 2013; Goswami & Dutta, 2016), which found that gender plays an important role in explaining students' behaviour in e-learning. So, the moderating effect of gender gives another explanation for the shape of the nonlinearity in Figure 4.4b and Figure 4.5b, which decreases sharply at the group that is less satisfied with the perceived VD, which is the female category. Moreover, the moderating effect of gender gives another explanation for the shape of the nonlinearity in Figure 4.4b and Figure 4.5b, which decreases sharply at the group that is less satisfied with the perceived VD or CE, which is the female category.

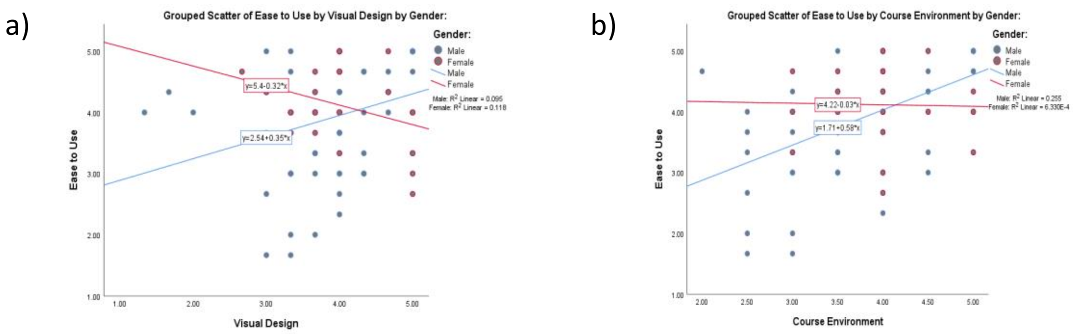

Figure 4.13 Interaction plot (Gnender as a Moderator), (a) gender moderate relation VD, EoU, (b) gender moderate relation CE, EoU.

4.5.3 SMART phone and desktop usage as a moderator

In Figure 4.14a, the students' group who use SMART phones have a steep linear slope in an increasingly positive trend according to the graphic linking CQ with EoU with linear relation. This implies that those who use SMART phones are more interested in CQ relevant to the content being up to date, organized in a logical sequence, and supportive in learning via the web to be effortless. In Figure 4.14b, the students' group who do not use desktop computers have a steep linear slope in an increasingly positive trend according to the graphic linking CE with EoU with non-linear relation. And this implies that those who use desktop computers are less interested in the environment of the courses being helpful in active learning, critical thinking development, idea sharing, and contextual learning which make them perceive their learning via the web to be effortless. According to Basri et al. (2018), two-thirds of the students use SMART phones accessing the internet to pass pass time, fifteen percent of them admit that they get help at least via one of the social media platforms in solving their homework. This study can attribute the effect of modern IT gadgets, like laptops and smartphones that may contribute significantly to collaborative communication, and the students' perceptions toward the system the contents and the environment of its courses.

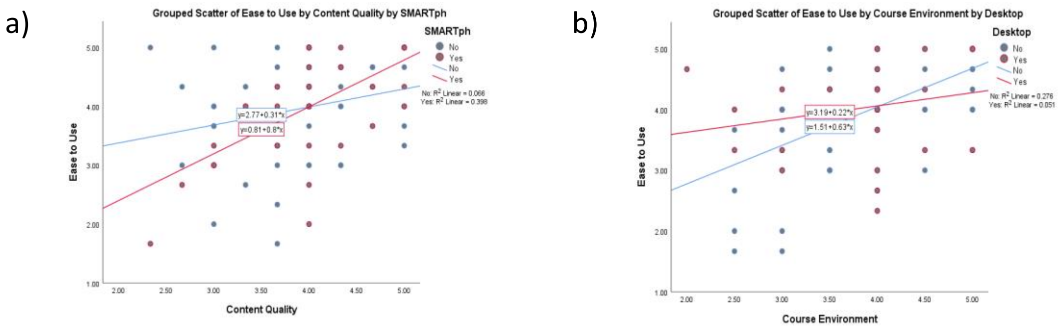

Figure 4.14 Interaction plot (technology Usage as a Moderator), (a) SMART phone usage moderate relation CQ, EoU, (b) desktop usage moderate relation CE, EoU.

4.5.4 Time as a moderator

In Figure 4.15a and Figure 4.15b, the students' group who spend fewer hours accessing the internet or learning course content via the web has a steep linear slope in an increasingly positive trend according to the graphic linking CQ with U or EoU with linear relations. This implies some students are more interested in CQ relevant to the content being up to date, organized in a logical sequence, and supportive in learning via the web to be effortless, than students who spend more hours online. This is consistent with the Baki et al. (2021) study which highlights the effect of time on the acceptance of the system, concluding that the students' perceived usefulness will increase while spending a short time in the system.

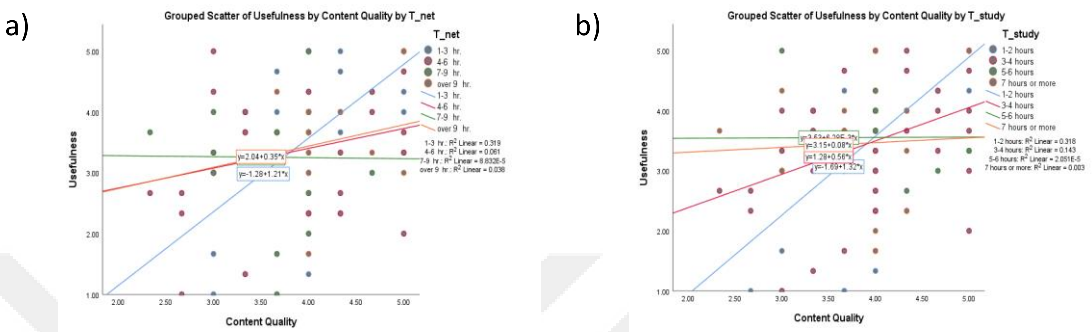

Figure 4.15 Interaction plot (time as a moderator), (a) time moderate relation CQ, U, (b) time moderate relation CQ, EoU.

4.6 Conclusion

The majority of research related to the acceptance of technology based on TAM tested the linear relationship between the factors and introduced a linear model in which the interpretation coefficient varies or may exclude predictors, while the non-linear correlation may prove the existence of the correlation. So, this study moved from the traditional direct effect relationship between predictor HCI main factors and ease of use and usefulness of e-learning to more complex non-linear relationships between such predictors towards online learning.

The acceptance of collaborative web-based learning as e-learning has become concerns of educational institutions' awareness in the light of the spread of the COVID-19 pandemic and rapid technological developments. So, this study sheds light on the effect of HCI factors on TAM main factors, where the extended TAM has been most frequently used to predict the user intentions toward the actual use. The empirical findings in this study support the hypotheses for establishing non-linear relationships between two sets of related factors associated with HCI and EoU, and U of e-learning in Kadir Has University in Turkey, as a case study.

The use of nonlinearity instead of linearity in this study highlighted that 85% of the relationships in this model prove to be nonlinear, the magnitudes of β increase up to 25.7% and R^2 increases up to 44.7%; some relationships between HCI factors and perceived ease of use reversed the direction of influence from negative to positive or vice versa; 76.5% have a U-shape or inverted U-shape with one "turning point" while 23.5% have an S-shape with two "turning points;" some constructs that have a medium-size effect on the acceptance of technology negatively affect the level of perceived ease of use when it is improved as factors (VD, SQ, and LInt); some constructs are significant in the nonlinear correlation while not significant in the linear regression test as the effect of LInt as well as the perceived U on students' performance (GPAs and grades in the courses).

Analytical approaches support nonlinearity. This provides alternative interpretations that are crucial to different contexts of technology acceptance models without overstating or understating the main effects that followed in the common linear method. Thus, these results lead to finer explanation power, more understanding of the complex links which exist between the dependent and independent variables, more help in revealing unrevealed nonlinear relationships in linear assumptions, and more explanation power that captures the more sophisticated integrating effects. Accordingly, we believe that this study will contribute to developing a more comprehensive insight into explaining the complex nature of user perceptions when researchers relax traditional linearity postulations and to carefully consider the non-linearity assumptions to reveal the potential complex non-linear relationships within the key constructs in technology acceptance models, which will be tested in their studies.

4.6.1 Implications of the study

The results of modelling the non-linearity can provide a suitable basis for developing the interaction between humans and computers in terms of the online learning environment and help explain the ease of use and the usefulness of this kind of technology.

Both individuals and society may realize the benefits of using web-based collaborative learning when designers, developers, and HCI experts consider the system characteristics, the users' attributes and beliefs, and the use outcomes, as important determinants of any web-based technology adoption. Even in other contexts, and after the research was conducted with nonlinearity, it allows us to better understand the process of technology acceptance in education institutions. From the society's perspective, a well-designed computer interface should take into consideration users' limitations and human categories. This is what the research may contribute to in terms of developing modern interactive and collaborative systems that serve learners and provide safety and necessary facilities for them in the light of the Covid-19 pandemic. Further, it allows them to become independent, self-determining, and more interactive away from the constraints of time and place.

In some nonlinear relationships, the curve has a negative tendency regarding the students' perception about some HCI factors as VD and CE that affect EoU They moved from strongly disagree to neutrality, where the curve gets steeper and in the opposite trend of the linear relationship. It is not suitable for improvement in students' perceptions towards many factors without regard to the nature of those students and their characteristics or levels, which is highlighted and explained in cases by the moderator variables. For example, even if the convictions of the same group of students, whose initial impressions were poor about the attractiveness of the interface design and consistency of layout, are improved to a positive impression, the increase in the perception of ease of use will remain below the required level and less than before. So, non-linear results give more explanation about the great proportion associated with the common variance within students' groups compared to linear regression results, whether there are differences in their characteristics or in their levels of perceptions. Hence, the effects of these differences have been revealed by nonlinearity.

Furthermore, this study introduces a comprehensive conceptual model based on non-linear relationships. Hence four kinds of models (logarithmic, luadratic, cubic, and S-curve) out of ten were proven as functions of non-linear effects compared to linear relationships based on R^2, adjusted R^2 and SEE values. So, we can conclude that cubic models draw relationships between EoU or CE, and U, also between VD, CE, LInt, or CES, and EoU, in addition between LInt or U and students' grades; quadratic models draw relationships between VD, CE, or SQ, and U, also between SQ or CSC, and EoU;

S-curve models draw relationships between LInt, Nav, or CSC, and U, also between LInt and students’ GPAs; while logarithmic model draws relationship between CES and U.

The developed model in this study provides practical implications to the decision-makers in the educational institutions to convince students to use e-learning in an effective way. They should consider the following recommendations if they seek to achieve a higher level of actual use: improving the attractiveness of e-learning interface design (mean=3.5), enhancing the system quality to be fun in operating and subjectively pleasing (mean=3.29), developing the online assessment tools and the technical feedback about students' performance (mean=3.65), consequently enhancing the students' perceptions about the usefulness of e-learning systems as an alternative teaching method that competes with the traditional teaching in a classroom.

Moreover, this study leads to the conclusion that technology usages such as (using a SMART phone to access Khas Learn, and the time spent on the internet or online studying), and personal information such as (gender) moderate the relationships between some HCI factors and U or EoU. SMART phone usage affects two relationships (CE → EoU, or CQ → EoU); the time spent on the internet or online studying affect only one relationship (CQ → U); and gender affects two relationships (VD → EoU, or CE → EoU). Therefore, researchers working in the field of technology acceptance should consider these moderators to increase the explanatory power of the TAM main factors.

Finally, researchers working in the field of technology acceptance and universities should dedicate more consideration to the male students who rated the U, CES, CQ more, and Nav less than females; the students who aged between 18-20 and rated SQ more than those older than 20; the students who attended low interactive courses like "GE204" and rated U, CES, CE, LInt, and Nav less than those who attended the interactive courses as "IE205".

5. INTEGRATING TAM WITH UTAUT

Integrating Technology Acceptance Model with UTAUT to Increase the Explanatory Power of the Effect of HCI on Students' Intention to Use E-Learning System and Perceive Success

This part of the study aimed to investigate the potential human-computer interaction factors (HCI) affecting students' behavioural intentions (BI) to use the e-learning system and perceive success. This part proposes a comprehensive model, integrating the technology acceptance model (TAM) and unified theory of acceptance and use of technology (UTAUT). The data were collected via an online survey conducted on 232 students utilizing the Khas Learn system of Kadir has University in Turkey. The proposed hypotheses were tested by multi-linear regression in SPSS v26. The results were obtained via a quantitative method illustrate that the main predictors of students' success are behaviour intention, ease of use, usefulness, visual design, and learner interface interactivity which explained 47.9% of perceived success in using the system. While, the main predictors of behaviour intention are facilitating condition, effort expectancy, ease of use, and usefulness which explained 68.9% of the variance in continuance intentions to use e-learning. Therefore, the empirical findings provide strong backing to the integrative approach between UTAUT and TAM extended by HCI main factors, which showed a high explanatory power in accepting e-learning technology and leads to enhance the students' success.

5.1 General Problem Statement and the Third Part Objectives

This part of the study seeks to explore the extent to which students are prepared to continue using e-learning, which has become imposed due to the COVID-19 pandemic. Therefore, in the first part of this research, the impact of students' experiences in using the system on the relationship between human-computer interaction and the acceptance of this technology was studied, and then the impact of all these constructs on the perception of success. While the linear approaches did not detect the effect of the proposed model constructs on the students' GPAs or grades, the second part of this study was able to prove a non-linear relationship.

The lower or higher level of perceptions or expectations obtained via actual use may lead to motivating or demotivating the continuity usage intentions. Has been proven, that perceived usefulness is a strong secondary predictor of users’ intention to continue using new technology, while satisfaction was supported as the strongest determinant (Bhattacherjee, 2001). Furthermore, usefulness does not tap into the self-efficacy dimension as ease of use (Han & Conti, 2020). Where the results of the first part of this study show that SE has a very weak positive effect on U, while it has a significant positive effect on EoU. This is consistent with most previous studies in which only a TAM model is used according to Abdullah and Ward (2016). Moreover, perceived usefulness enhances users' subjective probability that the use of an information system will improve their performance (Davis et al., 1989), thus the rational instrument or the component of their use decision is captured. Besides perceived U, perceived facilitating conditions (FC) represent the post-acceptance expectations, also they are primary motivators of any new technology adoption (Han & Conti, 2020). So, the integration of these constructs may subsequent continuance decisions.

Most research on the role of UTAUT and TAM, in terms of continuance intention and perceived success, did not examine the inter-relationships among the different constructs of TAM and UTAUT, extended by HCI main factors. Therefore, this part will integrate TAM with UTAUT theory to examine the structural relationship of perceived U, EoU and users’ behaviour intentions, to study the inter-relationships among the different dimensions of students’ intentions, and to test their influences on users’ continuance intention toward web-based learning.

The proposed third model is an evolution of TAM and UTAUT approaches by taking advantage of both to validate the intentions of end-users post actual use of e-learning. Integration of TAM and UTAUT theories is suitable for considering technological, social, and psychological aspects. Whereas the TAM focuses on the technological challenges, the UTAUT covers the social psychological aspects (Robles-Gómez et al., 2021). Studies that analyze users' intentions to actively use information technology are usually conducted using TAM or UTAUT (Kar et al., 2021).

Additionally, the modifications of the original TAM constructs have been proposed in the first part to measure the quality of web-based courses and the interaction with the system. Another extension of TAM pays attention to the perceived interface design and perceived interactivity influences on the students' acceptance and academic performance. Taherdoost (2018) revealed that UTAUT has higher explanatory power than other models, whereas behavioural intention, which has been included in this part, would imply a high quality of the system (Robles-Gómez et al., 2021). In this sense, the traditional TAM factors is used in, in conjunction with UTAUT factors.

Venkatesh et al. (2003) found that eight out of several models explained around 17% to 53% of the variance in behavioural intention to use information systems or information technology. But, the UTAUT outperformed these models explaining about 70% of the variance in users' intention if using the same data (Venkatesh et al. 2003) and explaining 50% of the variance in technology use (Venkatesh et al. 2012).

Furthermore, to achieve user-friendly, design enhancement associated with their main factors should be considered (Issa & Isaias, 2015). The factors that embedded in interactivity need to be concerned by specialists in the field of HCI to achieve safety and user-friendly system, which are: environmental, organizational, system functionality, health and safety components, comfort, constraints, task, productivity factors, accessibility, and users. Many studies have focused on user characteristics in the context of e-learning, but there is a scarcity of studies that have tested the impact of system and computer characteristics in the context of interactivity and technology adoption as the sequencing of system usage steps or the instructions may be read by the user differently from the designer's intent (Lewis & Mack, 1982). Moreover, the online learning environment, the design of appropriate courses, and the use of the computer as a complex device highlight the necessity to help the user by adapting this system to become more flexible, efficient, functional, usable, and easy to use, and designing that in the system correctly (Rozanski & Haake, 2017), taking into account the users' perceptions. This raises the importance of extending the integration of TAM and UTAUT constructs with HCI factors and testing the effect of these relations on SS.

Understanding the core knowledge in the HCI fields, e-technology acceptance, and user behaviour which have become a growing trend recently, it is necessary to study the effects of integrating related factors on students' intention to continue using e-learning and their perceived success in the time of COVID-19 pandemic. So, this study aims to:

- Determine the factors that are associated with two theories of technology acceptance and linked with human-computer interaction main factors that positively affect students' e-learning acceptance and success.
- Find correlations between the integrated UTAUT and TAM main factors which were extended by HCI and self-assessment factors and determine the strength of negative or positive influence on the acceptance of e-learning and students' success.
- Determine which of these factors have the most significant impact on the adoption of e-learning.
- Create a comprehensive third model that explains why students in Turkish universities accept e-learning and thus success based on the integration of two theories.

To answer these questions. First, the researcher adopted the first structured questionnaire, which was developed in the first part of this study and then added items related to UTAUT constructs. Second, a third conceptual model, related to factors affecting students' intention and their perceptions, was constructed in terms of integrated two theories of technology acceptance. Third, the structured survey was designed to collect sample data, and empirical analysis was conducted to validate the theoretical model using multilinear regression analysis via SPSS-v25 software. To validate the results Cronbach's alpha was employed. Fourth, the respondents' grades were traced on the system via their ID numbers. Finally, the constructs of the proposed model were discussed, and some recommendations were put forward to improve the interactivity and interaction between humans and computers, e-learning acceptance, and perceived success from technical and perception aspects, based on students' experiences in using the system.

5.2 Research Model and Hypotheses Development

The objective of this part of this study was to analyze the main impact of the proposed third model which focuses on studying the influences among two technology acceptance (UTAUT and TAM) constructs during the students' learning process. According to Robles-Gómez et al. (2021), there were no studies in the literature that evolved models from an integrated TAM and theories.

A first TAM model approach, which was extended by HCI factors and affected SS, was given in part one. And an exploratory data analysis has also been conducted in deep as a previous step, to be the basis of the third part of this work.

Then, a set of hypotheses among integrated TAM and UTAUT approaches are defined, analyzed, and validated as follows:

5.2.1 UTAUT main constructs

UTAUT approach covers the social-psychological aspects in the third proposed model, and their impact on the continuance intentions of students post actual use of e-learning. This theory joined four core constructs, including facilitation conditions, effort expectancy, performance expectancy, and social influence, beside behaviour intention to actual use (Venkatesh et al., 2003).

In this study, the focus will be on two factors, namely EE and FC, since they are related to technical aspects of the system in terms of ease of use, free of effort in usage, as well as its infrastructure quality that should be well-equipped to support. These factors are expected to be most related to the development of human-computer interaction.

Effort expectancy is defined as "the ease of using a system" (Kaplan & Gürbüz, 2020). While **facilitating conditions** refer to the degree to which users believe that the organizational and technical infrastructure is well-equipped to support the utilization of the new technologies, products, or services (Kaplan & Gürbüz, 2020). **Behavioural intention** is known as the momentary antecedent of usage behaviour which determines the individual's readiness to continue a particular behaviour (Al-rahmi et al., 2019). To test the effect of these constructs on behavioural intention and their perceived success we derived the variables: **EE1**=the (KHAS Learn) is easy to use; **EE2=** it easy for a user to become skillful (Balkaya & Akkucuk, 2021), **EE3**=and become proficient at using (KHAS Learn) (Tan, 2013); **EE4**=the learning activities with (KHAS Learn) are clear and understandable (Balkaya & Akkucuk, 2021); **FC1**=the user has the resources, **FC2**=and knowledge necessary to use (KHAS Learn) (Alshehri et al., 2020); **FC3**=the user think that using (KHAS Learn) fits well with the way they like to learn (Tan, 2013); **FC4**=If users have problems in using (KHAS Learn), they could solve them very quickly (Tan, 2013); **BI1**=users intend to use (KHAS Learn) in their future learning activities; **BI2**=and they would use (KHAS Learn) to improve their skills and knowledge; **BI3**=the users plan to use (KHAS Learn) in the next semester (Tan, 2013) if it is voluntary.

Moreover, a UTAUT meta-analysis has been conducted to compare the effect size of its constructs were analyzed in 69 studies between 2008 and 2018 and to examine the difference by comparing the results with previous studies applied meta-analysis on 37 studies between 2003 and 2011. The results were as follows: the effect of EE on BI showed a large effect size (d=0.457, p<0.001; d=0.436, p<0.001) respectively, where the average sample size=273; and also showed a large effect size of the influence of FC on BI (d=0.440, p<0.001; d=0.377, p<0.001), where the average sample size=252 (Hwang & Lee, 2018). Therefore, one of the objectives of this study is to find out if there is an increase in the effect size of each of these constructs if they are integrated with other model constructs in the context of technology acceptance. From this perspective, we developed hypotheses as follows:

Hypothesis 1: The integration of these constructs: TAM factors (EoU and/or U), FC, and EE have a direct positive influence on the perceived behaviour intention for using e-learning system.

Hypothesis 2: The integration of these constructs: TAM factors (EoU and/or U), perceived interface design factors (CE, SQ, CQ, and/or VD), and SE have a direct positive influence on the perceived facilitating condition for using e-learning systems.

Hypothesis 3: The integration of these constructs: TAM factors (EoU and/or U), perceived interactivity factors (LInt, AcS, Nav, CSC, and/or CES), and SE have a direct positive influence on the perceived facilitating condition for using e-learning systems.

Hypothesis 4: The integration of these constructs: TAM factors (EoU and/or U), perceived interface design factors (CE, SQ, CQ, and/or VD), and SE have a direct positive influence on the perceived effort expectancy for using e-learning systems.

Hypothesis 5: The integration of these constructs: TAM factors (EoU and/or U), perceived interactivity factors (LInt, AcS, Nav, CSC, and/or CES), and SE have a direct positive influence on the perceived effort expectancy for using e-learning systems.

Hypothesis 6: Facilitating condition has a direct positive influence on the perceived behaviour intention for using e-learning system.

Hypothesis 7: Effort expectancy has a direct positive influence on the perceived behaviour intention for using e-learning system.

5.2.2 TAM main constructs

According to the research objectives, the factors related to TAM should be integrated with UTAUT main constructs to enhance the explanatory ability of the model. Furthermore, for e-learning systems, different factors associated with HCI should be used to extend the integrated model. From this perspective, we developed hypotheses as follows:

Hypothesis 8: The integration of these constructs: TAM factor (EoU) and perceived interface design factors (CE, SQ, CQ, and/or VD) have a direct positive influence on the perceived usefulness of using e-learning systems.

Hypothesis 9: The integration of these constructs: TAM factor (EoU) and perceived interactivity factors (LInt, AcS, Nav, CSC, and/or CES) have a direct positive influence on the perceived usefulness of using e-learning systems.

Hypothesis 10: The integration of these constructs: perceived interface design factors (CE, SQ, CQ, and/or VD) and SE have a direct positive influence on the perceived ease of use of e-learning systems.

Hypothesis 11: The integration of these constructs: perceived interface interactivity factors (LInt, AcS, Nav, CSC, and/or CES) and SE have a direct positive influence on the perceived ease of use of e-learning systems.

5.2.3 Students' success

To test the effect of UTAUT, TAM, and HCI constructs on SS, we derived the variables: SS1=students confident about their knowledge of the subject that they learned through (Khas Learn), SS2= will get better marks when the course is taught online than in the classroom, SS3=have the ability of easier balance between education, family, work, and COVID-19 pandemic safety requirement (May, 2019), SS4=feelling better able to engage and interact with the course material (content) in online courses (May, 2019), SS5=and learning the course contents better when they are taught online than when they are taught in the classroom (Alawamleh et al., 2020). From this perspective, we developed hypotheses as follows:

Hypothesis 12: The integration of these constructs: TAM factors (EoU and/or U), perceived interface design factors (CE, SQ, CQ, and/or VD), perceived interface interactivity factors (LInt, AcS, Nav, CSC, and/or CES), and UTAUT factor (BI) have a direct positive influence on the students' success in using the e-learning system.

Based on grounded theory outcomes and reviewing previous research, the researcher proposed a conceptual model presented in Figure 5.1. This model shows UTAUT factors integrated with TAM's main factors that extended by HCI factors and SE, which have been proven by many researchers and experts as valid to predict users' intention toward e-learning's actual use. In this proposed model, the researcher wants to prove the effectiveness of these factors on the student success to be engaged in online courses and achieve many of the desired results.

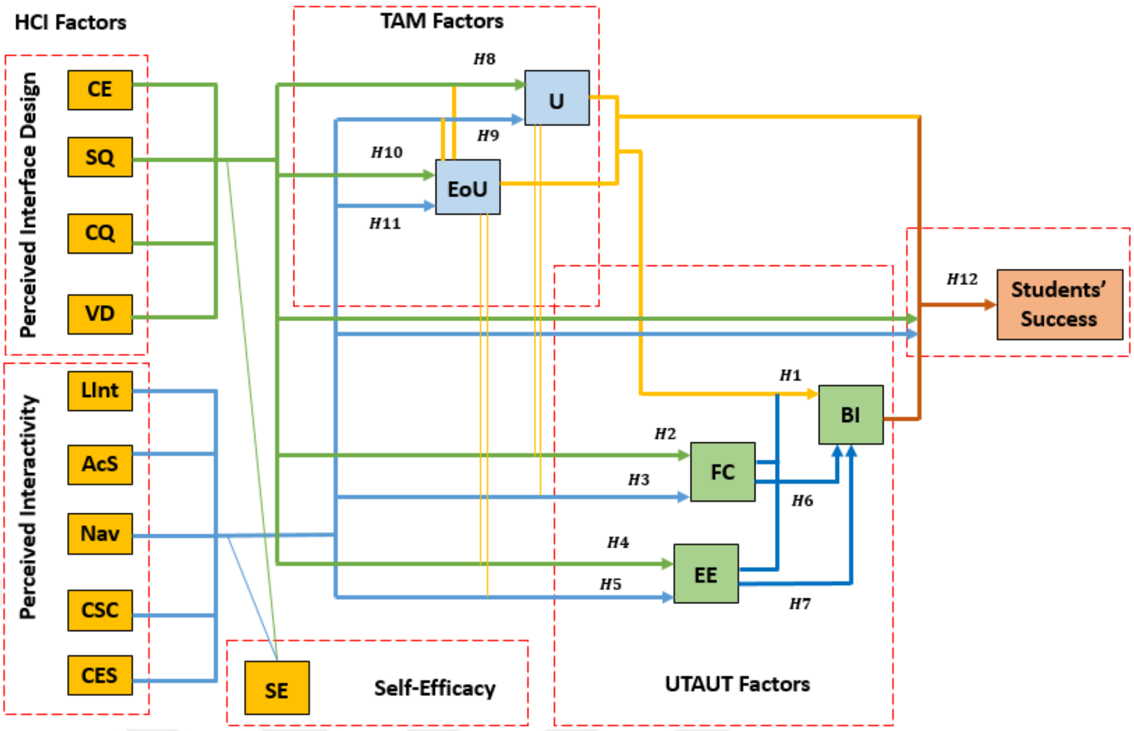

Figure 5.1 The researcher's proposed conceptual model (e-LASS2)

5.3 Methodology

In this part of this study, a survey was prepared and conducted to provide measures for factors included in the third proposed model. Finally, a conceptual model was developed using linear and multi-linear regression analyses.

5.3.1 Literature review:

A literature review was mainly designed to review existing literature and publications on the concept of UTAUT and the importance of integrating two theories in terms of post-technology acceptance and users' continuance intentions. Recent significant studies and reports were reviewed that related to critical factors associated with UTAUT and influencing behaviour intentions.

5.3.2 Data collection:

Data collection in this part includes the acquisition of structured survey data for empirical analysis in a quantitative method based on the regression analysis. The data required an appropriate tool as a survey technique to collect respondents' perceptions based on the Five-Likert scale to examine the correlation of the constructs of the proposed model. Data were collected via a survey method with a sample (n=232) of full-time undergraduate students at Kadir Has University. Furthermore, the researcher obtained the authority to track the development of students' grades in the online courses, their registration numbers were relied on. Moreover, the survey includes several items related to the first part added to its items that related to UTAUT's main factors. The first draft of the new questionnaire statements was dependent on specific previous empirical studies, and the viewpoint of experts. We reviewed the English version of the questionnaire, and adjustments were made. After that, we ensured the questionnaire's validity and reliability. Finally, we distributed this survey again. This fit with the quantitative approach.

5.3.3 Data analysis:

The researcher processed the data analysis using proper software called Statistical Package for the Social Science (SPSS-v25), which is useful for analyzing survey data and getting the causal relationships between questionnaire elements. SPSS fits the quantitative approach. The personal information, as well as different responses were analyzed based on the percentage of the frequency of participants; then, ANOVA tests were used to test correlations between qualitative and quantitative factors. Furthermore, linear, and multilinear regression analyses were used to test the research hypotheses and determine which ones would be supported.

5.4 Second Survey and its Quality

A second structured survey has been used to test the researcher's hypotheses. Quantitative variables were related to the UTAUT factors which integrated with TAM main factors and extended by HCI and SE were hypothesized to directly affect students' e-learning acceptance and indirectly student success (

Table **5.1**).

Table 5.1 Source of Questionnaire Statements (UTAUT Factors)

Factors	Variables	Questionnaire Statements	Source of Statements
Behavioural Intention (BI)	*BI1*	I intend to use (KHAS Learn) in my future learning activities	(Tan, 2013)
	BI2	I would use (KHAS Learn) to improve my skills and knowledge	(Tan, 2013)
	BI3	I plan to use (KHAS Learn) in the next semester, if it is voluntary	(Tan, 2013)
Perceived Facilitating Condition (FC)	*FC1*	I have the resources necessary to use (KHAS Learn)	(Alshehri et al., 2020)
	FC2	I have the knowledge necessary to use (KHAS Learn)	(Alshehri et al., 2020)
	FC3	I think that using (KHAS Learn) fits well with the way I like to learn	(Tan, 2013)
	FC4	If I have problems using (KHAS Learn), I could solve them very quickly	(Tan, 2013)
Perceived Effort Expectancy (EE)	*EE1*	I would find (KHAS Learn) is easy for me to use	(Balkaya & Akkucuk, 2021)
	EE2	I would find it easy for me to become skillful at using (KHAS Learn)	(Balkaya & Akkucuk, 2021)
	EE3	I would become proficient at using (KHAS Learn)	(Tan, 2013)
	EE4	My learning activities with (KHAS Learn) are clear and understandable	(Balkaya & Akkucuk, 2021)

5.4.1 Second survey validity and reliability:

The second survey reliability was tested by using Cronbach's alpha method which ranged from 0.700 to 0.937, bigger than 0.70 for all factors in the model (Table 5.2). Also, these results did not differ much from the results of the analysis of the first questionnaire, which indicates the reliability of this questionnaire and the consistency of its paragraphs. Thus, the research tool is considered reliable.

5.5 Results

The data collected via survey and analyzed by SPSS indicate that all statements are significant, and the inter-items are correlated.

Table 5.2 Reliability Static of Factors Influencing E-learning Acceptance and SS. (Survey2)

Factor	Items	Cronbach's Alpha (Survey2)	Cronbach's Alpha (Survey1)
VD	VD1, VD2, VD3	0.745	0.817
CE	CE1, CE2	0.727	0.753
SQ	SQ1, SQ2, SQ3	0.740	0.780
CQ	CQ1, CQ2, CQ3	0.846	0.737
Lint	LInt1, LInt2, LInt3	0.700	0.733
Nav	Nav1, Nav2, Nav3	0.884	0.735
AcS	AcS1, AcS2, AcS3, AcS4, AcS5, AcS6	0.853	0.748
CSC	CSC1, CSC2, CSC3	0.823	0.797
CES	CES1, CES2, CES3	0.817	0.806
SE	SE1, SE2, SE3	0.933	0.774
U	U1, U2, U3	0.936	0.911
EoU	EoU1, EoU2, EoU3	0.937	0.751
SS	SS1, SS2, SS3, SS4, SS5	0.852	0.859
EE	EE1, EE2, EE3, EE4	0.931	
FC	FC1, FC2, FC3, FC4	0.857	
BI	BI1, BI2, BI3	0.925	

5.5.1 Demographic and descriptive statistics:

The highest percentage of participants were males (63.8%), aged between 18-20 years old (78.7%), studying for one year at the university (63.8%), increased their GPAs from 3.50 to 4.00 (40.4%), and from 3.00 to 3.49 (36.2%), and expected to get AA (34.0%) and or BA (34.0%) grade letter (Table 5.3).

The results of short questions about technology usage in online courses show that 51.3% of the students spend between 1-3 hours on the internet per day; and 47.0% spend between 3-4 hours per week in their studies; 50.9% use from 9 to 12 platforms or tools; 87.1% use laptops to connect to Khas Learn while around 44.8% use SMART phones, 23.3% use desktops, or around 2.2% use tablets (Table 5.4).

Table 5.3 Personal Information (Second Survey Part One)

Personal Information		Frequency	Percent
Gender	Male	148	63.8%
	Female	84	36.2%
	Total	232	100%
Age	18-20	182	78.7%
	21-25	50	21.3%
	Total	232	100.0%
Academic Year	1 years	148	63.8%
	2 years	74	31.9%
	3 years or more	10	4.3%
	Total	232	100%
GPA	1.99 or less	6	2.1%
	2.00-2.49	24	10.6%
	2.50-2.99	24	10.6%
	3.00-3.49	84	36.2%
	3.50 or grater	94	40.4%
	Total	232	100%
The expected letter grade for the course	AA	79	34.0%
	BA	79	34.0%
	BB	40	17.0%
	CB	29	12.8%
	CC	5	2.1%
	DC	0	0.0%
	Total	232	100%

Table 5.4 Technology Usage (Second Survey Part Two)

Technology Usage		Frequency	Percent
Device used to connect Khas Learn	SMART Phone	104	44.8%
	Laptop	202	87.1%
	Desktop	54	23.3%
	Tablet	5	2.2%
Number of platforms, applications, or tools used in the course which web-based	1-4	20	8.6%
	5-8	79	34.0%
	9-12	118	50.9%
	13-16	15	6.5%
The daily time spent on the internet	1-3 hr.	119	51.3%
	4-6 hr.	74	31.9%
	7-9 hr.	25	10.8%
	over 9 hr.	14	6.0%
	Total	232	100%
The weekly time spent on the online course	1-2 hours	35	15.1%
	3-4 hours	109	47.0%
	5-6 hours	69	29.7%
	7 hours or more	19	8.2%
	Total		100%

To prove the effectiveness of e-learning, and its impact on SS, short questions were prepared, and students' courses grades were calculated. The results show that 72.4% of students considered the use of Khas Learn made them safe and secure; 44.8% prefer online o face-to-face learning; 53.1% expected their grades in the courses taught online; and 31.9% got grades in these courses greater than their GPA; besides, 55.2% got equal marks to their GPA (Table 5.5).

Table 5.5 Online Course Outcomes (Second Survey Part Three)

Personal Information		**Frequency**	**Percent**
Using Khas Learn makes me safe and secure.	Yes	168	72.4%
	No	15	6.5%
	I do not know	49	21.1%
	Total	232	100%
Preferring online to face to face learning	Yes	104	44.8%
	No	84	36.2%
	I do not know	44	19.0%
	Total	232	100%
Course grade as expected	Yes	123	53.1%
	No	109	46.9%
	Total	232	100%
Course grade equal or greater than student's GPA	Greater	74	31.9%
	Equal	128	55.2%
	Lower	30	12.9%
	Total	232	100%

5.5.2 Hypotheses testing

In order to determine the significant predictors of the main constructs in the proposed third model, multiple regression analysis has been performed, to detect the effect of integrated factors associated with technology acceptance, human-computer interaction, and self-assessments on the dependent factors, such as behavioural intention and students' success. For the formative construct, multicollinearity was checked, employing the variance inflation factors test (VIF). Where all VIFs should be under the conservative cut-off of 3.33 to indicate that multicollinearity is not a significant problem (Ifinedo et al., 2018).

The results obtained from multiple regression analysis showed that all hypotheses derived from integrated UTAUT factors with TAM factors and the integration of all these factors with HCI and SS were supported and proven to be significant determinants. Furthermore, the coefficient of determination of BI in the proposed conceptual model is 68.9% (adjusted R^2=0.689), where FC is the strongest determinant of BI. While, the coefficient of determination of SS in the proposed conceptual model is 47.9% (adjusted R^2=0.479), where U is the strongest determinant of SS.

5.5.2.1 Perceived behaviour intention results

The results of multi-linear regression analysis (Table 5.6) show that BI is jointly predicted by U, EoU, and FC (ρ=0.842, P<0.01), excluding EE. And VIF values for these predictors are less than 3.33, implying a lower probability of multicollinearity in the data. These TAM main factors (Eou and U) and UTAUT main factor (FC) explain BI by 68.9% (adjusted R^2=0.689), where FC is the strongest determinants of SS, whereas R^2 represents the coefficient of determination and ρ represents the coefficient of correlation. Thus, ***H1*** was supported.

Table 5.6 Multi-Linear Regression Test (The BI Predictors)

Y	X_i	*R*	R^2	adj. R^2	F	Sig.	ρ	t	Sig.	VIF
BI	U	0.842[a]	0.710	0.689	35.02	0.000[a]	0.275	2.028	0.049	2.358
	EoU						-0.128	-0.804	0.426	2.484
	FC						0.881	6.838	0.000	1.725

a. Predictors: (Constant), Facilitating Conditions, Usefulness, Ease of Use
b. Dependent Variable: Behaviour Intention

In addition, we tested the linear relationship between all the constructs (U, EoU, FC, and EE) and the dependent factor (SS) individually (R^2=0.377, R^2=0.292, R^2=0.680, and R^2=0.628 respectively), the results (Table 5.7) show that EE has a strong positive effect on BI (ρ=0.792, P>0.05), also FC has a very strong positive effect on BI (ρ=0.825, P<0.01). These two main factors (EE and FC) explain 62.8% and 68% variances of BI. Thus, ***H6*** and ***H7*** were supported. And we found that the explanatory power of the combined factors (U, EoU, and FC) in their impact on the dependent factor (BI) is higher (R^2=0.710) than the effect of EE (R^2=0.628) or FC (R^2=0.680) in the linear model.

Table 5.7 Linear Regression Test (The BI Predictors)

Dependent	Independent	R^2 (Linear)	ρ	F	Sig.	R^2 (Multi-Linear)
BI	U	0.377	0.614	27.256	0.000	0.710
	EoU	0.292	0.541	18.599	0.000	
	FC	0.680	0.825	95.698	0.000	
	EE	0.628	0.792	75.814	0.000	

5.5.2.2 Perceived facilitating condition results

The results of multi-linear regression analysis (Table 5.8) show that FC is jointly predicted by U, EoU, CE, SQ, and CQ (ρ=0.809, P<0.01), excluding VD and SE. And VIF values for these predictors are less than 3.33, implying a lower probability of multicollinearity in the data. These technology acceptance and interface design factors explain FC by 61.3% (adjusted R^2=0.613), where CQ is the strongest determinants of FC. Thus, ***H2*** was supported.

Table 5.8 Multi-Linear Regression Test (The FC Predictors)

Y	**X$_i$**	***R***	***R*^{2}**	***adj. R*^{2}**	**F**	**Sig.**	***ρ***	**t**	**Sig.**	**VIF**
FC	U	0.809[a]	0.655	0.613	15.57	0.000[a]	0.002	0.016	0.987	2.756
	EoU						0.183	1.199	0.237	2.590
	CE						-0.174	-1.506	0.140	2.032
	SQ						0.172	1.143	0.260	2.642
	CQ						0.690	4.613	0.000	2.491

a. Predictors: (Constant), Usefulness, Course Environment, Content Quality, Ease of Use, System Quality
b. Dependent Variable: Usefulness

Furthermore, FC is jointly predicted by AcS, CES, CSC, and SE (ρ=0.796, P<0.01) excluding U, EoU, Nav and LInt. And VIF values for these predictors are less than 3.33, implying a lower probability of multicollinearity in the data (Table 5.9). These interactivity and self-assessment factors explain FC by 59.8% (adjusted R^2=0.598), where AcS is the strongest determinant of FC. Thus, ***H3*** was partially supported.

Table 5.9 Multi-Linear Regression Test (The FC Predictors)

Y	**X$_i$**	***R***	***R*^{2}**	***adj. R*^{2}**	**F**	**Sig.**	***ρ***	**t**	**Sig.**	**VIF**
FC	AcS	0.796[a]	0.633	0.598	18.12	0.000[a]	0.598	3.510	0.001	1.956
	CSC						-0.051	-0.321	0.750	2.888
	CES						0.297	1.997	0.052	2.714
	SE						0.226	1.652	0.106	1.832

a. Predictors: (Constant), Self-Efficacy, Course Evaluation System, Accessibility and Support, Course Structure and Content
b. Dependent Variable: Usefulness

In addition, we tested the linear relationship between all the constructs (U, EoU, CE, SQ, and CQ) and the dependent factor (FC) individually (R^2=0.348, R^2=0.381, R^2=0.183, R^2=0.381, and R^2=0.614 respectively), and we found that the explanatory power of the combined factors in their impact on the dependent factor is higher (R^2=0.655). Also, between all the constructs (AcS, CES, CSC, and SE) and the dependent factor (FC) individually (R^2=0.542, R^2=0.324, R^2=0.402, and R^2=0.384 respectively), and we found that the explanatory power of the combined factors in their impact on the dependent factor is higher (R^2=0.633), see Table 5.10.

Table 5.10 Linear Regression Test (The FC Predictors)

Dependent	Independent	R^2 (Linear)	ρ	F	Sig.	R^2 (Multi-Linear)
FC	U	0.348	0.590	24.007	0.000	**0.655**
	EoU	0.381	0.617	27.711	0.000	
	CE	0.183	0.428	10.112	0.003	
	SQ	0.381	0.617	27.650	0.000	
	CQ	0.614	0.784	71.681	0.000	
FC	AcS	0.542	0.736	53.289	0.000	**0.633**
	CSC	0.324	0.569	21.556	0.000	
	CES	0.402	0.634	30.189	0.000	
	SE	0.384	0.620	28.034	0.000	

5.5.2.3 Perceived effort expectancy results

The results of multi-linear regression analysis (Table 5.11) show that EE is jointly predicted by EoU, CE, SQ, and CQ (ρ=0.817, P<0.01), excluding U, VD and SE. And VIF values for these predictors are less than 3.33, implying a lower probability of multicollinearity in the data. These technology acceptance and interface design factors explain EE by 63.7% (adjusted R^2=0.637), where EoU is the strongest determinants of EE. Thus, ***H4*** was supported.

Table 5.11 Multi-Linear Regression Test (The EE Predictors)

Y	X_i	R	R^2	adj. R^2	F	Sig.	ρ	t	Sig.	VIF
EE	EoU	0.817^a	0.668	0.637	21.15	0.000^a	0.540	-0.250	0.804	2.018
	CE						-0.027	0.085	0.933	2.559
	SQ						0.012	2.776	0.008	2.335
	CQ						0.384	4.131	0.000	2.085

a. Predictors: (Constant), Course Environment, Content Quality, Ease of Use, System Quality
b. Dependent Variable: Usefulness

Furthermore, EE is jointly predicted by AcS, CES, CSC, and SE (ρ=0.826, P<0.01) excluding U, EoU, Nav, and LInt. And VIF values for these predictors are less than 3.33, implying a lower probability of multicollinearity in the data. These interactivity and self-assessment factors explain EE by 65.2 (adjusted R^2=0.652), where AcS is the strongest determinant of EE (Table 5.12). Thus, ***H5*** was partially supported.

Table 5.12 Multi-Linear Regression Test (The EE Predictors)

Y	X_i	*R*	R^2	adj. R^2	F	Sig.	ρ	t	Sig.	VIF
EE	AcS	0.826[a]	0.682	0.652	22.55	0.000[a]	0.651	4.167	0.000	1.956
	CSC						0.210	1.440	0.157	2.888
	CES						-0.066	-0.486	0.630	2.714
	SE						0.307	2.448	0.019	1.832

a. Predictors: (Constant), Self-Efficacy, Course Evaluation System, Accessibility and Support, Course Structure and Content
b. Dependent Variable: Usefulness

In addition, we tested the linear relationship between all the constructs (EoU, CE, SQ, and CQ) and the dependent factor (EE) individually (R^2=0.591, R^2=0.261, R^2=0.357, R^2=0.512, and R^2=0.614 respectively), and we found that the explanatory power of the combined factors in their impact on the dependent factor is higher (R^2=0.668). Also, between all the constructs (AcS, CES, CSC, and SE) and the dependent factor (EE) individually (R^2=0.592, R^2=0.373, R^2=0.280, and R^2=0.477 respectively), and we found that the explanatory power of the combined factors in their impact on the dependent factor is higher (R^2=0.682), see Table 5.13.

Table 5.13 Linear Regression Test (The EE Predictors)

Dependent	Independent	R^2 (Linear)	ρ	F	Sig.	R^2 (Multi-Linear)
EE	EoU	0.591	0.768	64.903	0.000	**0.668**
	CE	0.261	0.511	15.892	0.000	
	SQ	0.357	0.597	24.965	0.000	
	CQ	0.512	0.716	47.224	0.000	
EE	AcS	0.592	0.769	65.204	0.000	**0.682**
	CSC	0.373	0.611	26.818	0.000	
	CES	0.280	0.529	17.487	0.000	
	SE	0.477	0.691	41.097	0.000	

5.5.2.4 Perceived usefulness results

The results of multi-linear regression analysis (Table 5.14) show that U is jointly predicted by EoU, CE, SQ, and CQ (ρ=0.798, P<0.01), excluding VD. And VIF values for these predictors are less than 3.33, implying a lower probability of multicollinearity in the data. These interface design factors and perceived ease of use explain U by 60.3% (adjusted R^2=0.603), where EoU is one of the strongest determinants of U. Thus, ***H8*** was supported. In addition, it is noticeable that the change in the interpretation coefficient adjusted R^2 has increased by 28.4% as the difference is (adjusted R^2= 0.603-0.319 =0.284) in comparison with the model tested in the first part. This means that the integration process has contributed to an increase in explanatory power.

Table 5.14 Multi-Linear Regression Test (The U Predictors)

Y	**X*i***	***R***	***R*²**	***adj. R*²**	**F**	**Sig.**	***ρ***	**t**	**Sig.**	**VIF**
U	EoU	0.798[a]	0.637	0.603	18.43	0.000[a]	0.490	3.190	0.003	2.085
	CE						0.070	0.545	0.589	2.018
	SQ						0.194	1.168	0.249	2.559
	CQ						0.273	1.677	0.101	2.335

a. Predictors: (Constant), Content Quality, Course Environment, Ease of Use, System Quality
b. Dependent Variable: Usefulness

Furthermore, U is jointly predicted by AcS, CES, and CSC (*ρ*=0.788, *P*<0.01) excluding Nav and LInt. And VIF values for these predictors are less than 3.33, implying a lower probability of multicollinearity in the data. These interactivity factors explain U by 59.4% (adjusted R^2=0.594), where CSC is the strongest determinant of U (**Table 5.15**). Thus, ***H9*** was supported. In addition, it is noticeable that the change in the interpretation coefficient adjusted R^2 has increased by 22.9% as the difference is (adjusted R^2= 0.594-0.365 =0.229) in comparison with the model tested in the first part. This means that the integration process has contributed to an increase in explanatory power.

Table 5.15 Multi-Linear Regression Test (The U Predictors)

Y	**X*i***	***R***	***R*²**	***adj. R*²**	**F**	**Sig.**	***ρ***	**t**	**Sig.**	**VIF**
U	AcS	0.788[a]	0.620	0.594	23.42	0.000[a]	0.414	2.423	0.020	1.582
	CSC						0.473	2.751	0.009	2.715
	CES						0.198	1.194	0.239	2.714

a. Predictors: (Constant), Course Evaluation System, Accessibility and Support, Course Structure and Content
b. Dependent Variable: Usefulness

In addition, we tested the linear relationship between all the constructs (EoU, CE, SQ, and CQ) and the dependent factor (U) individually (R^2=0.547, R^2=0.336, R^2=0.444, and R^2=0.468 respectively), and we found that the explanatory power of the combined factors in their impact on the dependent factor is higher (R^2=0.637). Also, between all the constructs (AcS, CES, and CSC) and the factor (U) individually (R^2=0.404, R^2=0.539, and R^2=0.463 respectively), and we found that the explanatory power of the combined factors in their impact on the dependent factor is higher (R^2=0.620), see Table 5.16.

Table 5.16 Linear Regression Test (The U Predictors)

Dependent	Independent	R^2 (Linear)	ρ	F	Sig.	R^2 (Multi-Linear)
U	EoU	0.547	0.740	54.381	0.000	**0.637**
	CE	0.336	0.580	22.774	0.000	
	SQ	0.444	0.666	35.867	0.000	
	CQ	0.468	0.684	39.660	0.000	
U	AcS	0.404	0.636	30.530	0.000	**0.620**
	CSC	0.539	0.734	52.513	0.000	
	CES	0.463	0.681	38.858	0.000	

5.5.2.5 Perceived ease of use results

The results of multi-linear regression analysis (Table 5.17) show that EoU is jointly predicted by CE, SQ, CQ, and SE (ρ=0.811, P<0.01), excluding VD. And VIF values for these predictors are less than 3.33, implying a lower probability of multicollinearity in the data. These interface design and self-assessment factors explain EoU by 62.5% (adjusted R^2=0.625), where SE is one of the strongest determinants of EoU. Thus, ***H10*** was supported. In addition, it is noticeable that the change in the interpretation coefficient adjusted R^2 has increased by 38.4% as the difference is (adjusted R^2= 0.625-0.241 =0.384) in comparison with the model tested in the first part. This means that the integration process has contributed to an increase in explanatory power.

Table 5.17 Multi-Linear Regression Test (The EoU Predictors)

Y	X_i	R	R^2	*adj.* R^2	F	Sig.	ρ	t	Sig.	VIF
EoU	CE	0.811[a]	0.658	0.625	20.175	0.000[a]	0.205	1.867	0.069	2.027
	SQ						0.141	1.002	0.322	2.552
	CQ						0.074	0.502	0.618	2.652
	SE						0.538	4.106	0.000	1.918

a. Predictors: (Constant), Self-Efficacy, Content Quality, Course Environment, System Quality
b. Dependent Variable: Ease of Use

Furthermore, EoU is jointly predicted by AcS, CES, CSC, and SE (ρ=0.872, P<0.01) excluding Nav and LInt. And VIF values for these predictors are less than 3.33, implying a lower probability of multicollinearity in the data. These interactivity and self-assessment factors explain EoU by 73.8% (adjusted R^2=0.738), where AcS is the strongest determinant of EoU (Table 5.18). Thus, ***H11*** was supported. In addition, it is noticeable that the change in the interpretation coefficient adjusted R^2 has increased by 34.7% as the difference is (adjusted R^2= 0.738-0.391 =0.347) in comparison with the model tested in the first part. This means that the integration process has contributed to an increase in explanatory power.

Table 5.18 Multi-Linear Regression Test (The EoU Predictors)

Y	X_i	*R*	R^2	*adj.* R^2	F	Sig.	ρ	t	Sig.	VIF
EoU	AcS	0.872[a]	0.761	0.738	33.36	0.000[a]	0.590	4.429	0.000	1.956
	CSC						0.328	2.635	0.012	2.888
	CES						-0.114	-0.977	0.334	2.714
	SE						0.327	3.051	0.004	1.832

a. Predictors: (Constant), Self-Efficacy, Course Evaluation System, Accessibility and Support, Course Structure and Content
b. Dependent Variable: Ease of Use

In addition, we tested the linear relationship between all the constructs (CE, SQ, CQ, and SE) and the dependent factor (EoU) individually (R^2=0.329, R^2=0.426, R^2=0.435, and R^2=0.540 respectively), and we found that the explanatory power of the combined factors in their impact on the dependent factor is higher (R^2=0.658). Also, between all the constructs (AcS, CES, CSC, and SE) and the dependent factor (EoU) individually (R^2=0.619, R^2=0.471, R^2=0.318 and R^2=0.540 respectively), and we found that the explanatory power of the combined factors in their impact on the dependent factor is higher (R^2=0.761), see **Table 5.19**.

Table 5.19 Linear Regression Test (The EoU Predictors)

Dependent	Independent	R^2 (Linear)	ρ	F	Sig.	R^2 (Multi-Linear)
EoU	CE	0.329	0.574	22.066	0.000	**0.658**
	SQ	0.426	0.652	33.337	0.000	
	CQ	0.435	0.659	34.599	0.000	
	SE	0.540	0.735	52.809	0.000	
EoU	AcS	0.619	0.787	73.063	0.000	**0.761**
	CSC	0.471	0.687	40.144	0.000	
	CES	0.318	0.564	20.985	0.000	
	SE	0.540	0.735	52.809	0.000	

5.5.2.6 Perceived student's success results

The results of multi-linear regression analysis (Table 5.20) show that SS is jointly predicted by U, EoU, BI, VD, and LInt (ρ=0.732, P<0.01). And VIF values for these predictors are less than 3.33, implying a lower probability of multicollinearity in the data. These interface design (VD), interactivity (LInt), technology acceptance (Eou and U), and behaviour intention factors explain SS by 47.9% (R^2=0.536, adjusted R^2=0.479), where BI and U are the strongest determinants of SS. Thus, ***H12*** was supported. In addition, it is noticeable that the change in the interpretation coefficient R^2 has slightly decreased by 0.5% as the difference is (R^2= 0.536-0.541 =-0.005) in comparison with the model tested in the first part. This means that the integration process has not contributed to an increase in explanatory power related to SS predictors.

Table 5.20 Multi-Linear Regression Test (The SS Predictors)

Y	X_i	R	R^2	adj. R^2	F	Sig.	ρ	t	Sig.	VIF
SS	U	0.732[a]	0.536	0.479	9.46	0.000[a]	0.537	2.505	0.016	2.811
	EoU						-0.463	-1.908	0.063	2.746
	BI						0.504	3.148	0.003	1.811
	VD						0.032	0.137	0.892	2.057
	LInt						0.270	1.092	0.281	2.452

a. Predictors: (Constant), Learner Interface Interactivity, Behavior Intention, Visual Design, Ease of Use, Usefulness
b. Dependent Variable: Student's Success

In addition, we tested the linear relationship between all the constructs (U, EoU, BI, VD, and LInt) and the dependent factor (SS) individually (R^2=0.373, R^2=0.143, R^2=0.418, R^2=0.209, and R^2=0.238 respectively), and we found that the explanatory power of the combined factors in their impact on the dependent factor is slightly lower the result of first part (R^2=0.536), see Table 5.21.

Table 5.21 Linear Regression Test (The SS Predictors)

Dependent	Independent	R^2 (Linear)	ρ	F	Sig.	R^2 (Multi-Linear)
SS	U	0.373	0.611	26.804	0.000	0.536
	EoU	0.143	0.379	7.538	0.009	
	BI	0.418	0.647	32.339	0.000	
	VD	0.209	0.457	11.899	0.001	
	LInt	0.238	0.488	14.032	0.001	

5.5.3 Third conceptual model testing results

Based on the testing results of all hypotheses (Table 5.22), the researcher determined the third conceptual model as a framework for the effect of HCI constructs on proposed approaches is an evolution of TAM and UTAUT theories by taking advantage of both to validate the intentions of students to continue using e-learning and perceived success, called e-LASS2 (Figure 5.2).

Table 5.22 Hypotheses Testing Results (Multi-Linear Regression Tests)

Hypo.	Regression	*R*	R^2	Adj. R^2	F	Sig.	Support
H1	(U, EoU, & FC) →**BI**	0.732	0.536	0.479	9.46	0.000*	Yes
H2	(U, EoU, CE, CQ, & SQ) →**FC**	0.809	0.655	0.613	15.57	0.000*	Yes
H3	(AcS, CES, CSC, & SE) →**FC**	0.796	0.633	0.598	18.12	0.000*	Yes Partially
H4	(EoU, CE, CQ, & SQ) →**EE**	0.817	0.668	0.637	21.15	0.000*	Yes
H5	(AcS, CES, CSC, & SE) →**EE**	0.826	0.682	0.652	22.55	0.000*	Yes Partially
H6	FC →**BI** (linear model)	0.825	0.680		95.70	0.000*	Yes
H7	EE →**BI** (linear model)	0.792	0.628		75.81	0.000*	Yes
H8	(EoU, CE, CQ, & SQ) →**U**	0.798	0.637	0.603	18.43	0.000*	Yes
H9	(AcS, CES, & CSC) →**U**	0.788	0.620	0.594	23.42	0.000*	Yes
H10	(CE, CQ, SQ, & SE) →**EoU**	0.811	0.658	0.625	20.18	0.000*	Yes
H11	(AcS, CES, CSC, & SE) →**EoU**	0.872	0.761	0.738	33.36	0.000*	Yes
H12	(U, EoU, VD, LInt, & BI) →**SS**	0.732	0.536	0.479	9.46	0.000*	Yes

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

5.6 Discussion

This part of the study suggests that students' continuance intentions, e-learning acceptance and the users' success, which we called e-LASS2, can serve as a starting point for generalizing in other contexts. In which the integration of UTAUT and TAM theories is being extended by HCI. The model explains approximately 68.9% of the variance of users' behaviour intentions and 47.9% of the variance in their perceived success and achievements post-technology acceptance during the learning process via web-based systems.

Although 76.6% of the students’ GPAs were high (equal or greater than 3 out of 4), about 31.9% of them, in the online courses, graded above their GPAs, and about 55.2% obtained equal grades to their GPAs. These outcomes illustrate the students' positive perceptions regarding perceived success through the practice of e-learning experience. Also, the results are close to the findings of the first part of this study. However, it was in favor of the second questionnaire in predicting the course grades by the students.

And most students considered using the "Khas Learn" system safe and secure, but less than the results of the first survey, where the difference is 10.1%, which coincided with the decline in the measures and precautions regarding the COVID-19 pandemic. Also, explain the decreasing percentage (44.8%) of those preferring to study online than face to face compared to the results of the first part. In addition, most of the students surveyed in this research area were in their first academic year (63.8%), where an increased percentage (36.1%) wanted to go through the study experience in traditional lectures.

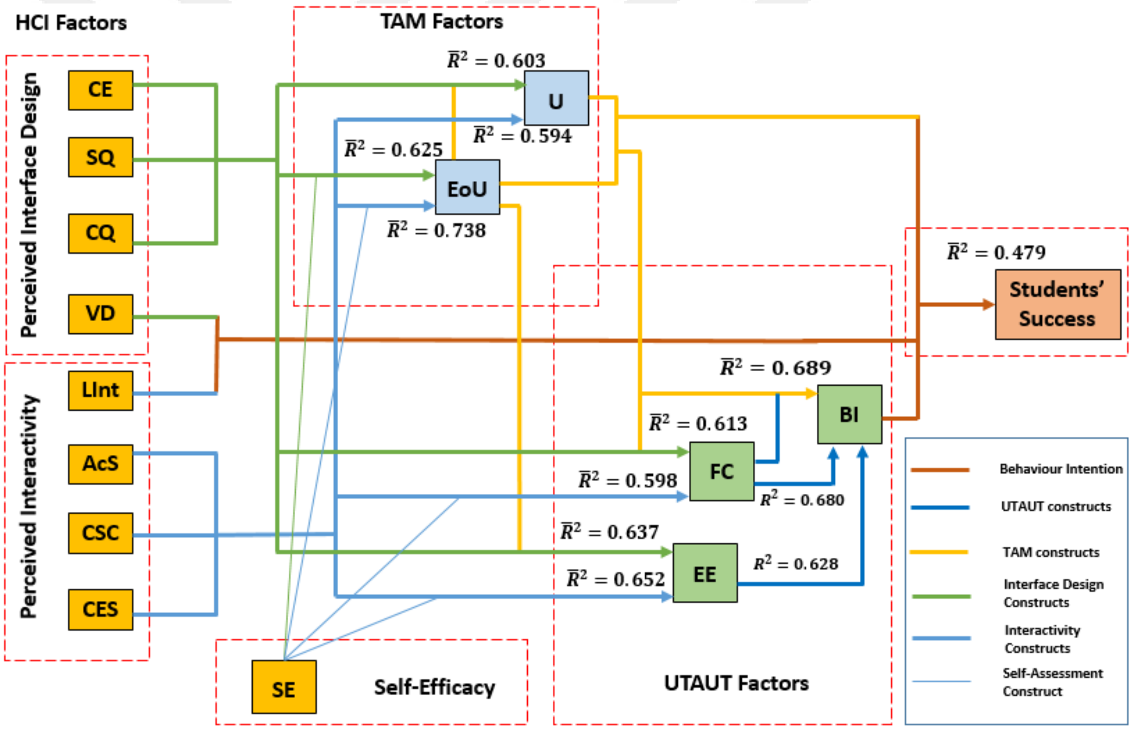

Figure 5.2 The researcher's proposed conceptual model (e-LASS2)

5.6.1 Hypotheses testing discussion

All hypotheses related to e-LASS2 are supported and significant at 99%, excluding H3, which was partially supported, where FC was not predicted by TAM constructs with the existence of perceived interactivity constructs. This indicates that all results are logical and can be adopted where the constructs of the developed e-LASS2 model explain 68.9% of the variance of behaviour intention (adjusted R^2=0.689) and 47.9% of the variance of student success (adjusted R^2=0.479).

Behaviour intention is predicted by four independent factors, out of which three integrated constructs derived from TAM and UTAUT, namely U, EoU, and FC, are proved by a multilinear model; and one construct derived from UTAUT, namely EE, is proven by a linear model. There are strong links between BI and its predictors, as expected from the exploratory analysis. Where students intend to use web-based learning in their future learning activities (mean=3.81) or in the next semester if it is voluntary (mean=3.91), to improve their knowledge and skills (mean=3.79). Facilitating condition is a key factor in the BI use of the (KHAS Learn) system. According to Tarhini et al. (2016), this construct plays as an organizational process in conjunction with web-based learning system implementation as a technological solution. This is if the student has the knowledge (mean=4.09) and resources (mean=4.17) necessary to use (KHAS Learn). These results are consistent with a study conducted by Almaiah et al. (2019), which concludes FC or EE, and the BI to use of technology systems are closely related.

Also, the findings suggest that when the e-learning system is easy to use (mean=4.17); and provides information that is easy to comprehend (mean=4.00), helps to learn effectively (mean=3.68), increases productivity in learning (mean=3.89), and improves learning performance (mean=3.85); furthermore, reflects the needs of students in terms of ease of getting information from the online courses (mean=4.04) without trouble to perform tasks (mean=4.17), becoming skillful (mean=4.13) and proficient at using the system (mean=4.17), and fits well with the way they like to learn (mean=3.85) or solve problems very quickly (mean=3.96), it could create high compatibility among those students to continue use and accept e-learning systems.

Moreover, the integrated technology acceptance constructs, namely U, FC, and EE, are predicted by three associated factors related to the perceived interface design, namely CE, SQ, and CQ, beside one construct derived from TAM, namely EoU, and U in case of FC, all are proved by a multilinear model; while EoU predicted by the same perceived interface design constructs beside one construct derived from self-assessment, namely

SE. There are strong links between TAM/UTAUT main constructs and their predictors, as expected from the exploratory analysis, where the coefficient of correlation between these constructs in the linear model ranged from (ρ=0.428) to (ρ=0.784), with an average (ρ=0.642). This means considering social, psychological and technological aspects to adopt and continue using e-learning, needs to consider the environmental factors as CE, which cover the web-based courses if it is helpful in active learning, idea sharing, critical thinking development, and contextual learning (mean=3.83); or it assist in self-directed work with the possibility of receiving feedback regardless of time and place (mean=3.83). Further, consider the organizational factors as CQ and SQ, which cover the overall content if it is up to date (mean=3.96), organized in a logical sequence (mean=4.11), sufficient to support learning (mean=3.89), and the materials are accessible without much effort (mean=4.15); and also if the system is fun to operate (mean=3.64) and its functions satisfactory (mean=3.80).

As that, the integrated constructs U, EoU, FC, and EE, are predicted by three associated factors related to the perceived interactivity, namely AcS, CSC, and CES, beside one construct derived from self-assessment, namely SE, excluding SE in the case of U where the correlation is very weak, according to Abdullah and Ward (2016); and all are proved by a multilinear model. There are strong links between TAM/UTAUT main constructs and their predictors in terms of interactivity, as expected from the exploratory analysis, where the coefficient of correlation between these constructs in the linear model ranged from (ρ=0.529) to (ρ=0.797), with an average (ρ=0.662). This means considering social, psychological and technological aspects to adopt and continue using e-learning, needs to consider the system accessibility and functionality factors as AcS, CSC and CES, which cover the content of online course if it is consistent with the course objectives (mean=4.09), and organized in a manner that helped students understand the underlying concepts (mean=3.89), and lead students to be confident that they will complete the skill or knowledge presented in these courses (mean=4.09); as well as the support provided by the system in which the help is always available (mean=3.94) and the E-mail enquiries can be made when there is a technical problem (mean=3.94), also the system is easy for them to log in (mean=4.47) and accessible from different browsers (mean=4.26), its manual provided the information that they need (mean=4.02), and its pages and other elements download quickly (mean=4.17); furthermore, if the system provides good online self-assessment tools such as online assignments (mean=4.02), measures the achievements of learning objectives (mean=3.83), and presents useful feedback on a performance about online exams (mean=3.64). All of this requires the presence of self-assessment constructs to integrate with perceived interactivity constructs derived from HCI, where the students feel confident using the system even if there is no one around to show them how to experience web-based learning (mean=4.47) and use its contents (mean=4.36), also learning how to use online courses easily (mean=4.47).

Regarding the perceived success, this construct is predicted by five associated factors related to the TAM/UTAUT main constructs, namely U, EoU, and BI; besides one construct derived from perceived interface design, namely VD, and other from perceived interactivity, namely LInt; which is proved by a multilinear model. There are intermediate links between SS and its predictors in terms of the integration of two theories which extended by HCI factors, as expected from the exploratory analysis, where the coefficient of correlation between these constructs in the linear model ranged from (ρ=0.379) to (ρ=0.647), with an average (ρ=0.523). This means considering the users' perceived success in using e-learning needs to consider the social, psychological and technological aspects post technology acceptance. So, when the students have a perceived continue intention that beyond the actual use, and can realize ease of use and the usefulness of the system, use the systems' map to locate their needed information (mean=3.81), track their status regarding their grade points or relative status in a class (mean=3.87), and access online teaching materials anytime they want (mean=4.13); further, the consistency of systems' colors and layouts (mean=3.98), the readability of their texts and graphics (mean=4.13), and the attractiveness of their interfaces' design (mean=3.62); all of this will enhance the students confident about their knowledge of the subject that they learned through e-learning system, (mean=3.87), their convictions that they can obtain better marks when the course is taught online than in the classroom (mean=3.15), their sense of being better able to participate and interact with course material in online courses (mean=3.30), their awareness that learning the course contents will better when they are taught online than when they are taught in the classroom (mean=2.77), and their abilities of easier balance between work, education, and family (mean=3.30). These distinguish e-LASS2 from the previous model, e-LASS, where both VD and LInt contribute to the interpretation of the variance in perceived success besides the acceptance of e-technology. In addition, Nav was ignored from the third model due to its weak significant effect when integrating with other constructs, although has been proven as one of the important influential factors within HCI constructs in the first model.

5.7 Conclusion

End-users intentions in terms of technological, psychological, and social aspects are an important base in determining the continuity of the use of e-learning. Which, educational institutions, such as universities, should take into account when making improvements and developing web-based educational systems, especially in the conditions of the outbreak of the COVID-19 pandemic. This part of the study applied the integration of TAM and UTAUT theories for explaining the key relevant constructs to human-computer interaction and technology acceptance, in order to construct a new theory, grounded in the first part of data in this study, that is derived to predict students' continuance intentions toward e-learning’s actual use and predict their perceived success, post-adoption of the system. While TAM focused on the technological aspects, the addition of UTAUT constructs (behaviour intentions, facilitating conditions, and effort expectancy) to the model covered the social-psychological aspects.

As a result of surveying 232 undergraduate students who used the "KHAS Learn" system, the most critical factors that influence students’ behaviour intentions to continue using the system and their perceived success were identified, and a new conceptual model has been developed as a valid and a powerful tool called "e-LASS2," that assists in enhancing the learning and teaching process via a web-based system.

The outcomes, obtained through a survey strategy, proved that the main predictors of behaviour intention are facilitating condition, usefulness, and ease of use which explained 68.9% of the variance in continuance intentions to use e-learning (adjusted R^2=0.689). While, the direct influences of FC and EE on BI cannot be ignored in the model, because they explained 68% and 62.8% of the variances in BI (R^2=0.680, R^2=0.628 respectively). In addition, the main predictors of SS are behaviour intention, usefulness, ease of use, learner interface interactivity, and visual design which explained 47.9% of perceived success when using the web-based system (adjusted R^2=0.479).

Furthermore, the findings revealed some points which should be considered. First, the main predictors of EoU, EE, and FC in terms of perceived interactivity are AcS, CEC, and CES related to the systems' functionality, integrated with SE, together explained (73.8%, 65.2%, and 59.8% respectively) variances in e-learning acceptance (adjusted R^2=0.738, 0.652, and 0.598 respectively); while, explained 59.4% of the variance in perceived U, without SE. Second, the remaining main predictors of EE, FC, and U in terms of perceived interface design are CE, CQ, and SQ related to organizational and environmental aspects, integrated with EoU, together explained (63.7%, and 61.3% respectively) variances in e-learning acceptance (adjusted R^2=0.637, R^2=0.613 respectively); while, explained 62.5% of the variance in perceived EoU, when integrated with SE. So, the combined or integrated independent factors in their impact on the dependent factors as BI, EE, FC, U, and EoU, in the proposed third model, will increase the explanatory power. Third, although the majority of respondents to the second survey (44.8%) support the online study on face-to-face, a good percentage of them prefer to try face-to-face classroom lectures (36.2%); this was in contrast to the results of the first part of this research. Since most of those registered in the study courses among the respondents are first-year students at the university (63.8%), at a time when the COVID-19 precautions were relaxed. This requires enhancing the interactive aspect of web-based e-learning systems, developing user interface as well as course content, and raising the system quality to be more functional and accessible. Finally, students' achievement is still better through e-learning, as 87.1% have obtained grades equal to or greater than their GPAs. So, universities should pay more attention to the educational content and its quality to increase the student's awareness regarding the course contents that will be better when they are taught online than when they are taught in the classroom, where they rated this variable less than others (mean=2.77).

6. THE RESEARCH SUMMARY

Conclusion, Recommendations, Limitations and Future Work

6.1 Conclusion and Recommendations

The spread of the COVID-19 pandemic leads to changes in educational and learning methods and methodologies under technological advancement and the need to reduce costs. Worldwide educational institutions face the challenge of promoting students' engagement in an e-learning environment to maintain the continuity of web-based education, especially in Turkey. So, there is a need to increase user percentages in the e-learning process under difficult circumstances. To address learners' preferences it is necessary to consider system features and human factors, which goes beyond technology adoption. In this study, the effect of human-computer interaction (HCI) factors on e-learning acceptance and students' success (SS) were considered, and the influence of students' activities as a moderator on the relationship between the constructs in the proposed model that we called "e-LASS" was investigated. Furthermore, the non-linear relationships between these constructs were explored. Moreover, this study upgraded the first model, developing a comprehensive model that we called "e-LASS2," integrating the TAM/UTAUT main factors, extended by HCI, and proven their effect on students' achievements as their grades in the courses and their continuance intentions to use the system.

The result of surveying 103 undergraduate students from Kadir Has University in Turkey, whose grade and activity logs were accessible, show that most of the hypotheses were supported. The most critical HCI factors that interact with students' success through using online learning systems, and influence ease of use and usefulness of e-learning, were identified. And logs which represent users' activities via the system as a moderator were proven. Thus including "logs" as a moderator would increase the explanatory power of the effect of HCI factors on e-learning acceptance and SS in the model. Together are explain 54.9% of the variance in SS, and usefulness is the strongest determinant. While the non-linear models (cubic, quadratic, logarithmic, and s-curve) in the second part of this study performed a better explanation of the complex nature of user perceptions and interpretation of the sophisticated causal links when compared to linear models. Although e-LASS can serve as the starting point for the generalization of the model in other contexts, the use of nonlinearity highlighted that 85% of the relationships in related models were proven to be nonlinear, whereas the magnitudes of β can increase up to 25.7% and R^2 can increases up to 44.7%, also some constructs are significant in the nonlinear correlation while not significant in the linear regression test as the effect of LInt and U on students' performance as their GPAs and grades in the courses. More than 60% of learners via web-based systems are convinced of the feasibility of e-learning in achieving success, which practically translated to higher grades than their GPAs. Moreover, the findings from conducting the second survey on 232 undergraduate students who utilised the Khas Learn system of Kadir Has University revealed that the main predictors of SS are behaviour intention, ease of use, usefulness, learner interface interactivity, and visual design. All these constructs explained 47.9% of the variances in SS. In addition, the main predictors of behaviour intention are facilitating condition, usefulness, and ease of use which explained 68.9% of the variance in continuance intentions to use e-learning. Also, the direct influences of FC and EE on BI cannot be ignored in the model, because they explained 68% and 62.8% of the variances in BI.

Both individuals and society may realize the benefits of using web-based collaborative learning when designers, developers, and HCI experts consider the system characteristics, the users' attributes and beliefs as an important determinant of any web-based technology adoption. And also the system environment's development to enhance the users' engagement and continuity in using the system. Besides that, universities should pay more attention to the educational content and its quality to increase the student's awareness regarding the course content that will be better when they are taught online than when they are taught in the classroom, where they rated this variable less than others. In general, this study contributes to the existing literature on HCI, e-learning acceptance, and SS by linking engineering and technical issues with social sciences; helping decision-makers and specialists enhance the user experience in terms of e-learning actual use and success from the user point of view, especially in the light of the COVID-19 pandemic; and highlighting the importance of technology acceptance factors in enhancing student success, not solely their intention and attitudes toward actual use of any web-based systems.

6.2 Limitations and Future Work

The limitations of this study are for generalizing the outputs in different sectors. The scope of this study is associated with HCI’s main factors, which investigated the undergraduate students' views at Kadir Has University, whose grades were accessible to the researcher, in accepting the online learning system. The proposed model requires to be used in several sectors to validate its results. Further studies could be conducted to test or investigate the perceptions of instructors and other employees in different sectors. There is also a need to study the correlation between students' activities on the web and their grades based on the nature of these interactive activities.

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APPENDIX A

Appendix A.1. Items Used in This Study

Table A.1 Source of Questionnaire Statements (HCI and TAM Main Factors)

Factors	Variables	Questionnaire Statements	Source of Statements	Mean
Perceived Usefulness (U)	*U1*	Online courses in (Khas Learn) improve my learning performance	(Binyamin et al., 2020); (Pituch & Lee, 2006)	3.46
	U2	Online courses in (Khas Learn) help me learn effectively	(Binyamin et al., 2020)	3.41
	U3	Using the (Khas Learn) increases my productivity in learning	(Abbad et al, 2009); (Davis 1986); (Pituch & Lee, 2006)	3.48
Perceived Ease of Use (EoU)	*EoU1*	Getting information from the online courses in (Khas Learn) was easy	(Abbad et al, 2009); (Davis 1986); (Pituch & Lee, 2006)	3.92
	EoU2	I have no trouble in using (Khas Learn) to perform tasks that I needed	(Cho et al., 2009)	3.86
	EoU3	The (Khas Learn) provides information that is easy to comprehend	(Cho et al., 2009)	4.07
Visual Design (VD)	*VD1*	Text, colors, and layout used in (Khas Learn) are consistent	(Binyamin et al., 2020)	4.03
	VD2	Text and graphics of (Khas Learn) are readable	(Binyamin et al., 2020)	4.14
	VD3	The interface design of (Khas Learn) is attractive to me	(Binyamin et al., 2020)	3.50
Course Environment (CE)	*CE1*	The course webpage on (Khas Learn) was helpful in active learning, critical thinking development, idea sharing, and contextual learning	Developed by reshercher	3.79
	CE2	The course webpage on (Khas Learn) assisted in self-directed work with the possibility of receiving feedback regardless of time and place	Developed by reshercher	3.87
Content Quality (CQ)	*CQ1*	Overall, the content of (Khas Learn) is up to date	(Binyamin et al., 2020)	3.98
	CQ2	Overall, the content of (Khas Learn) is organized in a logical sequence	(Binyamin et al., 2020)	3.87
	CQ3	Overall, there is sufficient content in (Khas Learn) to support my learning	(Binyamin et al., 2020)	3.89
System Quality (SQ)	*SQ1*	The (Khas Learn) is fun to operate and subjectively pleasing	(Lin, 2010)	3.29
	SQ2	I am satisfied with (Khas Learn) functions	(Liaw, 2008); (Chang et al., 2011)	3.65
	SQ3	I can gain access to any course materials in (Khas Learn) without much effort	(Kim & Lee, 2014)	3.92
Learner-Interface	*LInt1*	Students can use (Khas Learn) map to locate the needed information.	(Chou, 2003)	3.83

Interactivity (LInt)	*LInt2*	Students can track their status regarding their grade points or relative status in a class.	(Chou, 2003)	3.87
	LInt3	Students can access online teaching materials anytime they want	Developed by resercher	4.20
	LInt4	I can start using (Khas Learn) easily with some online help	(Binyamin et al., 2020)	4.09
	LInt5	The (Khas Learn) enable students to accomplish course tasks more quickly	(Lin, 2010)	3.98
Navigation (Nav)	*Nav1*	The navigational structure of (Khas Learn) is convenient for me	(Binyamin et al., 2020)	3.89
	Nav2	It is easy for me to find the information I need in (Khas Learn)	(Binyamin et al., 2020)	4.02
	Nav3	Links in (Khas Learn) are working satisfactorily	(Binyamin et al., 2020)	4.01
Course Evaluation's System (CES)	*CES1*	(Khas Learn) provides good online self-assessment tools (e.g., online exams, quizzes, or assignments)	(Binyamin et al., 2020)	3.90
	CES2	The assessment tools (e.g., online exams, quizzes, or assignments) in (Khas Learn) measure my achievements of the course learning objectives	(Binyamin et al., 2020)	3.68
	CES3	I received useful feedback on my performance about online assignments and exams	Developed by researcher	3.65
Course Structure and Content (CSC)	*CSC1*	The online course content is consistent with the course objectives	Developed by researcher	4.22
	CSC2	I am confident that I will comprehend the information or skill presented in this online course	Developed by researcher	3.99
	CSC3	The online course was organized in a manner that helped me understand the underlying concepts	Developed by researcher	3.87

Appendix A.2 Kadir Has University Grades and Symbols

Table A.2 Academic Credit System and European Credit Transfer System in Kadir Has University (Grades and Symbols)

Khas Grade (Letter)	ECTS Grade	Coefficient	Definition	Definition In Evaluation System
AA	A	4	(Excellent)	90-100
BA	B	3,5	(Very Good)	80-89
BB	B	3	(Good)	70-79
CB	C	2,5	(Satisfactory)	60-69
CC	C	2	(Fair)	50-59
DC	D	1,5	(Conditional Pass)	45-49
DD	E	1	(Conditional Pass)	40-44
FF	F	0	(Fail)	0-39
FF	FX	0	(Fail)	0

Source: https://international.khas.edu.tr/academic-credit-system-and-ects-in-kadir-has-university-92

APPENDIX B

Appendix B.1. The Survey

Part 1: Personal Information:

Gender: ☐ Male ☐ Female

Age: ☐ 18-20 ☐ 21-25 ☐ 26-29 ☐ over 29

Academic Year: How many years?

☐ 1 year ☐ 2 years ☐ 3 years ☐ 4 years or more

Your GPA: ☐ < 2 ☐ 2-2.5 ☐ 2.5-3 ☐ 3-3.5 ☐ > 3.5

The course you register now: ☐ GE204 ☐ IE205

My expected letter grade from this course is:

☐ FF ☐ DD ☐ DC ☐ CC ☐ CB ☐ BB ☐ BA ☐ AA

Part 2: Technology Usage:

What type of devices you use to connect to Khas Learn? (You can choose more than one answer)

☐ SMART Phone ☐ Laptop ☐ Desktop ☐ Tablet

The name of University platforms, applications, or tools which web-based, that I used in my course: (you can choose more than one answer)

	Sparks		**Word**
	Webmail (Outlook)		**Excel**
	MyKhas		**PowerPoint**
	Khas Learn		**Access**
	AutoCAD		**R**
	MATLAB		**Minitab**
	Phyton		**SPSS**
	BigBlueButton		**OneDrive**
	Microsoft Teams		**Dropbox**
	Gmail		**Google Drive**

The ones I familiar with:

……………………………………………………………………………………..

How much time do you spend using internet per day for acquiring information daily? (Other than social media)

☐ 1-3 ☐ 4-6 ☐ 7-9 ☐ over 9

How much time do you spend on this online course daily?

☐ 1 hour ☐ 2 hours ☐ 3 hours ☐ 4 hours or more

Using Khas Learn Online Courses from my home, makes me safe and secure. Especially after the outbreak of Covid-19 pandemic.

☐ Yes ☐ No ☐ I Do not Know

I prefer online learning to face-to-face learning because of Covid-19 pandemic.

☐ Yes ☐ No ☐ I Do not Know

Part 3: HCI, TAM, Self-Assessment and Students' Success factors:

Item	Questionnaire Statements	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
VD1	Text, colors, and layout used in (Khas Learn) are consistent					
VD2	Text and graphics of (Khas Learn) are readable					
VD3	The interface design of (Khas Learn) is attractive to me					
CE1	The course webpage on (Khas Learn) was helpful in active learning, critical thinking development, idea sharing, and contextual learning					
CE2	The course webpage on (Khas Learn) assisted in self-directed work with the possibility of receiving feedback regardless of time and place					
CQ1	Overall, the content of (Khas Learn) is up to date					
CQ2	Overall, the content of (Khas Learn) is organized in a logical sequence					
CQ3	Overall, there is sufficient content in (Khas Learn) to support my learning					
SQ1	The (Khas Learn) is fun to operate and subjectively pleasing					

SQ2	I am satisfied with (Khas Learn) functions					
SQ3	I can gain access to any course materials in (Khas Learn) without much effort					
LInt1	Students can use (Khas Learn) map to locate the needed information.					
LInt2	Students can track their status regarding their grade points or relative status in a class.					
LInt3	Students can access online teaching materials anytime they want					
LInt4	I can start using (Khas Learn) easily with some online help					
LInt5	The (Khas Learn) enable students to accomplish course tasks more quickly					
Nav1	The navigational structure of (Khas Learn) is convenient for me					
Nav2	It is easy for me to find the information I need in (Khas Learn)					
Nav3	Links in (Khas Learn) are working satisfactorily					
AcS1	E-mail enquiries can be made when there is a technical problem with (Khas Learn)					
AcS2	The online help of (Khas Learn) is always available					
AcS3	The (Khas Learn) manual provides the information I need					
AcS4	It is easy for me to login to (Khas Learn)					
AcS5	I can access (Khas Learn) from different browsers					
AcS6	The pages and other elements of (Khas Learn) download quickly					
CES1	(Khas Learn) provides good online self-assessment tools (e.g., online exams, quizzes, or assignments)					
CES2	The assessment tools (e.g., online exams, quizzes, or assignments) in (Khas Learn) measure my achievements of the course learning objectives					
CES3	I received useful feedback on my performance about online assignments and exams					
CSC1	The online course content is consistent with the course objectives					
CSC2	I am confident that I will comprehend the information or skill presented in this online course					
CSC3	The online course was organized in a manner that helped me understand the underlying concepts					

U1	Online courses in (Khas Learn) improve my learning performance					
U2	Online courses in (Khas Learn) help me learn effectively					
U3	Using the (Khas Learn) increases my productivity in learning					
EoU1	Getting information from the online courses in (Khas Learn) was easy					
EoU2	I have no trouble in using (Khas Learn) to perform tasks that I needed					
EoU3	The (Khas Learn) provides information that is easy to comprehend					
SS1	I am confident about my knowledge of the subject that I learned through (Khas Learn)					
SS2	I will get better marks when the course is taught online than in the classroom					
SS3	Online courses provided an easier balance between education, family, work, and COVID-19 pandemic safety requirements					
SS4	I feel I am better able to engage and interact with the course material (content) in online courses					
SS5	I am learning the course contents better when they are taught online than when they are taught in the classroom					
SE1	I am confident using the (Khas Learn) even if there is no one around to show me how to do it					
SE2	I learned how to use (Khas Learn) online courses easily.					
SE3	I feel confident using (Khas Learn) online-teaching contents.					

Part 4: UTAUT Main Factors (Added to Second Survey)

Item	**Questionnaire Statements**	**Strongly Agree**	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**
FC1	I have the resources necessary to use (KHAS Learn)					
FC2	I have the knowledge necessary to use (KHAS Learn)					
FC3	I think that using (KHAS Learn) fits well with the way I like to learn					
FC4	If I have problems using (KHAS Learn), I could solve them very quickly					
EE1	I would find (KHAS Learn) is easy for me to use					

EE2	I would find it easy for me to become skillful at using (KHAS Learn)					
EE3	I would become proficient at using (KHAS Learn)					
EE4	My learning activities with (KHAS Learn) are clear and understandable					
BI1	I intend to use (KHAS Learn) in my future learning activities					
BI2	I would use (KHAS Learn) to improve my skills and knowledge					
BI3	I plan to use (KHAS Learn) in the next semester, if it is voluntary					

Thanks

CURRICULUM VITAE

Personal Information

Name and surname: Fareed AL-Sayid

Academic Background

Bachelor of Computer Science, AN-Najah National University, Palestine (2001)
Master of Engineering Management, AN-Najah National University, Palestine, (2015)

Works or Publications Derived from the Thesis

AL-Sayid, F., & Kirkil, G. (2022). Students' Web-Based Activities Moderate the Effect of Human-Computer-Interaction Factors on Their E-Learning Acceptance and Success During COVID-19 Pandemic. *International Journal of Human–Computer Interaction*, 1-24. https://doi.org/10.1080/10447318.2022.2087013

AL-Sayid, F., & Kirkil, G. (2022). Exploring Non-Linear Relationships between Perceived Interactivity or Interface Design and Acceptance of Collaborative Web-Based. *Education and Information Technologies*. (Accepted for publication)

AL-Sayid, F., & Kirkil, G. (2022). Integrating Technology Acceptance Model with UTAUT to Increase the Explanatory Power of the Effect of HCI on Students' Intention to Use E-Learning System and Perceive Success. (Under review)