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Exploring non-linear relationships between perceived interactivity or interface design and acceptance of collaborative web-based learning

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Abstract

The novelty of this 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 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. Our analysis shows that cubic models (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 (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 (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.

Keywords Human–Computer Interaction · Interface and Interactivity · Collaborative Learning · Usefulness · Ease of Use · Non-Linearity

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1 Introduction

The rapid growth of learning delivered via the web (e-learning) market worldwide, especially in higher educational institutions due to the COVID-19 pandemic since the beginning of 2020 (Bozkurt et al., 2020), and the employment of information systems (IS), and information and communication technologies (ICTs) in all aspects of administrative, financial, and educational processes in various universities turned out to be a good opportunity in education via internet-based open space, or collaborative web-based learning. To make e-learning systems successful, it is necessary to raise the user percentages through enhancing their interactions with computer-supported collaborative learning.

Universities in Turkey have moved in whole or in part to e-learning. This required web-based learning platforms and human–computer interaction in which students are the core of the process because it stands for their acceptance of the system after their conviction of the perceived usefulness and ease of use. The universities adopted web-based education policies, while the students did not have an opportunity to orient themselves and their attitudes toward the actual use of the system while indulging in a series of multimedia instructions and platforms (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 as a collaborative system are used extensively in education. They employ hypermedia and hypertext to allow numerous subjects to be related to each other in different ways. They introduce a map that provides an overall view of the information for direct navigation and access to mutual opinions. It also provides links for facilitated browsing. This requires computer-aided learning and web-aided course materials. The user may lose motivation to benefit from the capabilities of the system if it does not match the actual requirements of the tasks or duties that he/she seeks to implement (Rozanski & Haake, 2017). 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 models 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 and their perceptions, 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, linking with others, exchanging ideas, building professional personas, engaging in social commentary, offering guidance to others, and highlighting 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 viewpoint of students, on their achievement and perceived success.

Most of the research that covered the acceptance of e-learning relied on studying the characteristics of the user, but a few of them studied the characteristics of the system and the computer in terms of interaction and interactivity, and the effect of interaction with technical matters and online content. This is what Lewis and Mack (1982) discovered earlier that the step-by-step instructions were not quite as good because learners could read them differently from the designer's intentions. Moreover, it was believed a proper design of the interactive system makes the user need none or little help or training. But this is ideal even with the best systems currently available, in the view of Rozanski and Haake (2017), who mentioned 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.

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), and can be 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 learning achievement like 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 computer knowledge of learners, lack of awareness, personal touch, interest, and interaction due to connectivity issues.

Furthermore, most of the previous studies have investigated the linear relationships between two theories (Salam et al., 2021) 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 misjudgment of the most important impact for the results of the linear presumption. It can avoid the incorrect, incomplete, or partial explanation of the outcomes caused by linearity clarification (Titah & Barki, 2009). It can earn probable opportunities to be aware of the difficult relationship between the constructs of technology acceptance models. It can 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). It 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 being 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.

2 Theoretical framework

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 the 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 the Likert scale. They added the Likert scales in several 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 outcomes of respondents 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 nonlinear 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.

There are many advantages to using nonlinearity in models related to technology acceptance. Using nonlinearity-based models tend to produce specific path coefficients in the higher parts that are likely to be underestimated. For example, Habahbeh et al.'s (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 social influence SI 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).

Prom et al. (2022) pointed out that the assumption of linearity in some social relations often leads to misestimating 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 the 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.

2.2 Human computer interaction 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 they misunderstood the issues related to HCI (McCracken & Wolfe, 2004). For example, there 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.

To increase and maintain the users' responses, system should be designed carefully at the design stage. That is 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 in technology, organization, and work. As for psychology, user behaviour is analyzed by applying 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

Cluster	Factor	Conceptual theme	Cluster	Factor	Conceptual theme
1	2	System capability	7	13	Interface analysis
2	4	User interface design	8	5	Performance measurement and improvement
3	1	Task of the HCI system	9	12	Development of interaction
4	14, partial 15	Evaluation of interaction	10	7	Human reaction to technology
5	8, 10, partial 15	User acceptance of technology	11	Partial 3	Facial expression
6	11	Personalized system design	12	Partial 3, 6, 9	Effective interaction

Fig. 1 Studies on HCI (source: Shiau et al., 2016)

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 Fig. 1.

2.3 Technology acceptance models

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 & McLean, 2003), TRA, TAM, TAM2, TAM3 TPB, UTAUT, and UTAUT2, which were the most often used ones.

Theory of Reasoned Action (TRA) 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. Technology Acceptance Model (TAM) 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). The Theory of Planned Behavior (TPB) 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, the Unified Theory of Acceptance and Utilization of Technology (UTAUT) 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).

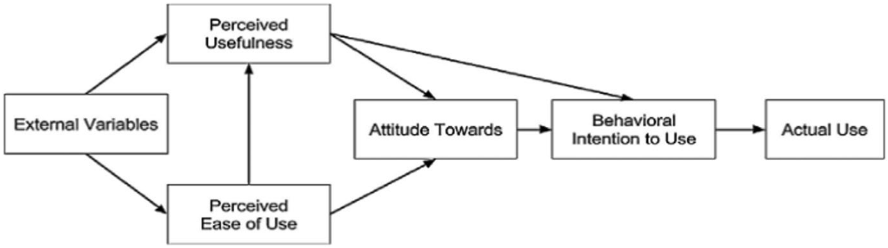


Fig. 2 TAM model of Chen et al. (2011)

TAM was developed by Davis et al. (1989) as an adaptation of the Theory of Reasoned Action (TRA) developed by Fishbein and Ajzen (1975) to find its origins in the field of social psychology. It has become one of the most influential research models in the subjects of information systems (IS) and information technology (IT) acceptance. It is widely applied through its main determinants, including perceived ease of use and perceived usefulness, to predict individuals' intention to use new technologies (Fig. 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).

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).

2.3.1 Perceived ease of use, and perceived usefulness

Perceived Ease of Use (EoU) is proven as the main predictor in TAM regarding the extent of users' belief about the free effort of technology usage (Davis et al., 1989). And it is highly related to the users' experiences of growth and their attitude toward the actual use of specific systems (Venkatesh, 2000). ***Perceived Usefulness (U)*** is another main factor that has been proven in TAM, which represents the users' belief about the improvement of work performance in system usage (Garcia, 2017; Venkatesh & Davis, 2000). Both these factors are affected by external variables (Chen et al., 2011).

A variety of research projects were conducted, and linear regression analyses were employed to prove the EoU and U relationship (Venkatesh, 2000; Venkatesh & 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.*

2.4 The subject of E-learning as a collaborative web-based learning

E-learning is the abbreviated form of two terms, electronic technology and learning online, and according to Rozanski and Haake (2017), it "is most often used for learning delivered via the web." It covers hardware and communication infrastructure as complex technical support; various forms of IS, IT, IT/IS, and ICT are used with the network architecture support of the internet and extranet (Koh & Maguire, 2009), and special software. It enables several online or web-based collaborative activities (Stevens, 2007). An online learning-friendly environment must include the students' attitudes toward actual use.

2.5 Studies conducted on E-learning acceptance and human computer interaction

Many studies were conducted in different universities and institutions in many countries in the context of HCI and web-based learning to enhance the acceptance of e-learning systems. Moreover, critical factors were examined and proven by using various models such as extended TAM (Al-Sayyed & Abdalhaq, 2016), which was considered the most used theory, followed by UTAUT (Šumak et al., 2011). Where the students are the most common user type, and perceived ease of use and usefulness tend to be the main factors that can influence their attitudes toward actual interaction with e-learning systems with the average path coefficient size ($\beta_{avg.}=0.400$) and around ($\beta_{avg.}=0.330$) concerning system quality based on 42 independent studies from different databases were reviewed by Šumak et al. (2011). While Abdullah and Ward (2016) explored that within 107 published articles the self-efficacy, subjective norm, enjoyment, computer anxiety, and experience are the most used ones to predict the usefulness with the average effect size for each were ranged between 0.070 and 0.452 (min $\beta_{avg.}=0.070$, max $\beta_{avg.}=0.452$), and to predict the ease of use with the average effect size were ranged between 0.195 and 0.352 (min $\beta_{avg.}=0.195$, max $\beta_{avg.}=0.352$). Later, Cidral et al. (2018) presented the timeline for the development of e-learning studies in different milestones (Fig. 3). Accordingly, before 2003, they focused on customization and course contents; from 2004 to 2006, they were concerned with the continued usage of e-learning platforms and their usability. Later, from 2007 to 2009, they focused on users' satisfaction level; from 2010 to

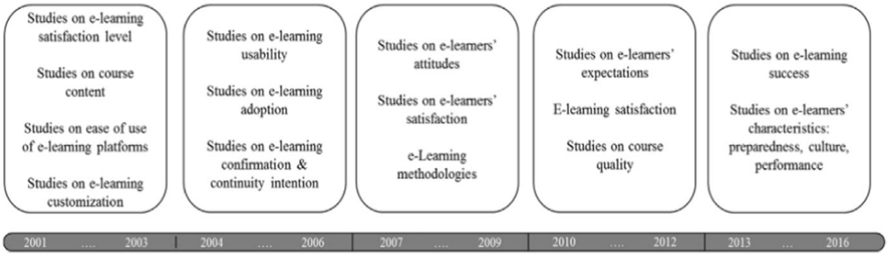


Fig. 3 Timeline for e-learning studies, source (Cidral et al., 2018)

2012, they considered learners' expectations and satisfaction; from 2013 to 2016, they highlighted the relationship between users' characteristics and e-learning success; finally, the latest studies focused on the role of interaction in e-learning success.

But in terms of interacting with the system in the context of mobile and HCI, El Said (2018) derived some factors as features of the design, the interrupt behaviour of users, content sharing, user control, and location-awareness notification used as platforms for interactive services. While in term of technical issues, Cahyono and Susanto (2019) demonstrated that the feelings of respondents are influenced by visual design components.

3 General problem statement and the paper 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 viewpoint of students, 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).

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

- Determine the factors that are affiliated with human–computer interaction fields and affect collaborative web-based learning acceptance.
- 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.
- Determine which of these factors have the most significant impact on the adoption of collaborative web-based learning in the proposed conceptual model.
- Create a comprehensive model that explains why students in Turkish universities accept collaborative web-based learning as e-learning.

4 Research model and hypotheses development

The researcher presented a conceptual model (Fig. 4) 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.

4.1 Human computer interaction main factors

According to Issa and Isaias (2015), the main factors and issues embedded in interaction and interactivity need to be considered by HCI specialists to achieve a user-friendly and safe system. They are organizational, environmental, health and safety

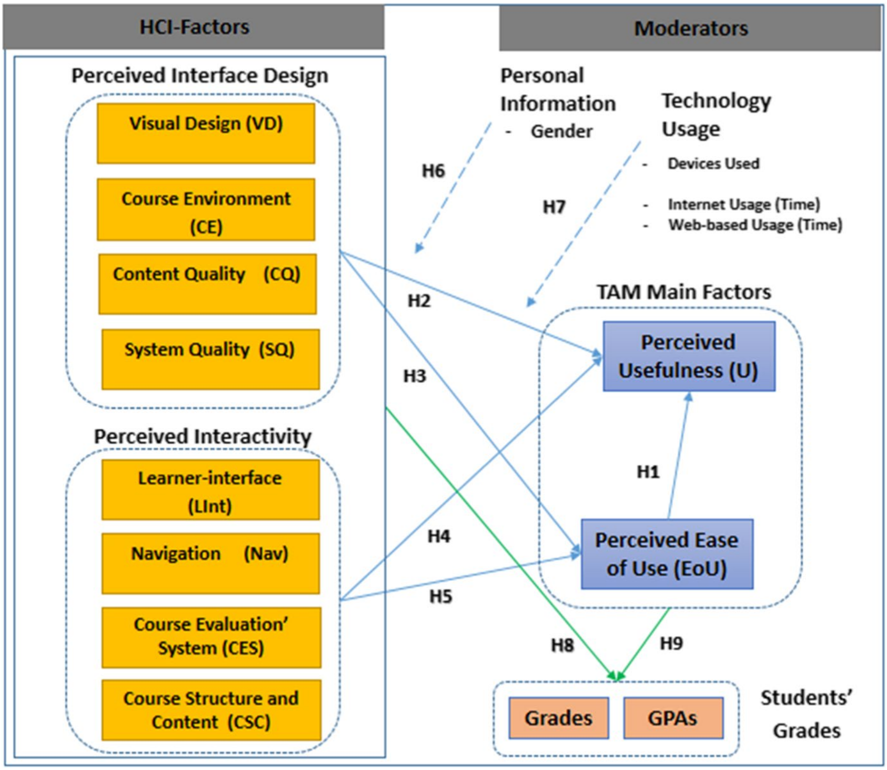


Fig. 4 The researcher's proposed conceptual model

components, users, comfort, task, constraints, system functionality, and productivity factors.

Out of organizational factors, which cover job design, politics, and work organization that affect content quality, we derived these variables (see Table 35 of the supplementary material): 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 (Binyamin et al., 2020).

Out of 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.

Out of 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).

Out of 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 (Lin, 2010), SQ2 = its functions satisfactory (Liaw, 2008; Chang et al., 2011), SQ3 = and the course materials are accessible without much effort (Kim & Lee, 2014).

Out of 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.

Out of 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) a map to locate their needed information (Chou, 2003); Lint2 = track their status regarding their grade points or relative status in a class (Chou, 2003); LInt3 = access online teaching materials anytime they want; LInt4 = start to use it easily with some online help (Binyamin et al., 2020); LInt5 = and accomplish course tasks more quickly (Lin, 2010). 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.

Out of 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 (Pituch & Lee, 2006; Abbad et al., 2009); EoU2 = without trouble to perform tasks needed (Cho et al., 2009); EoU3 = and the system provides information that is easy to comprehend (Cho et al., 2009).

Out of 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 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 (Binyamin et al., 2020); 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 (Pituch & Lee, 2006); U2 = helps to learn effectively (Binyamin et al., 2020); U3 = and increases productivity in learning (Abbad et al., 2009).

4.1.1 Perceived interface design

Interface design must be helpful for users in accomplishing online tasks in terms of HCI. This theory covers many factors linked to the users' perception, most notably perceived ***Visual Design (VD)***, whose components such as colour, media, and layout are considered the most influential on the students' performance in online learning or using a website (Cahyono & Susanto, 2019); perceived ***Course Environment***

(CE), which should be a supportive design for specific needs of students in accessing servers and instructional materials (Veglis & Barbargires, 2001); perceived ***Content Quality (CQ)***, which should include sufficient materials (Binyamin et al., 2020) designed in manifold formats and types (Tran, 2016) to raise e-learning responses (Salloum et al., 2019); and perceived ***System Quality (SQ)***, which considered the users' technical measure to IS (Gable et al., 2008), and its content quality (Alla, 2013), and the functional and technical quality of IT (Navimipour & Zareie, 2015), as a critical success factor in adopting e-learning according to IS success model (DeLone & McLean, 2004).

To investigate the importance of enhancing the 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.*

4.1.2 Perceived interactivity

Martins et al. (2019) introduced a model that raises awareness regarding the students' perception of the extent of their recognition for the continued use of the system related to their satisfaction with the interaction with IS. Interactivity in an online educational context refers to the activity between learners and computers in the context of HCI (Issa & Isaias, 2015). This theory involves many factors associated with users' perception, most notably perceived ***Learner-Interface Interactivity (LInt)***, which allows users to interact with systems through a web menu that includes, for example, control bars, icons, and maps that were designed to be user-friendly (Eraslan Yalcin & Kutlu, 2019); use preference (Liu et al., 2010); and ease in finding the right way to learn (Mouakket & Bettayeb, 2015); perceived ***Navigation (Nav)***, which is one of the intellectual cores that approaches the usability impeded in HCI (Shiau et al., 2016), also contributes to the effectiveness of website (Issa & Isaias, 2015). Its importance will appear when navigating between different web pages or browsing contents through scrolling, tapping, and swiping gestures, although the previous studies could not present a deep understanding of how specific user capabilities and characteristics can affect their navigation behaviour (Li & Luximon, 2019); perceived ***Course Evaluation System (CES)***, in which students interact with online self-assessment in the educational process based on ICT (Ćukušić et al., 2014); and perceived ***Course Structure and Content (CSC)***, which refers to the e-learning systems' flexibility and functionality where instructional materials, completing quizzes and tests via websites, and error-free quality in submitting the homework is accessed (Tran, 2016).

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 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).

Binyamin et al. (2020) stated that several studies proved gender as a moderator when technology acceptance models, such as TAM, UTAUT and UTAUT2 are applied. Binyamin et al. (2020) state that several studies proved gender as a moderator when technology acceptance models such as TAM, UTAUT and UTAUT2 are applied. A lot of previous studies focused on testing the interrelationships between the extended factors of the TAM model and its main factors, but a scarcity of research examined the descriptive statistics such as ages, or the experiences such as technology usage, as potential moderators (Kim et al., 2019). In the light of these potential variables that would increase the explanatory power of the EoU and U as a moderator, the researcher developed the following hypotheses:

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.*

4.3 Students' academic outcomes, grade point averages and course grade

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 the names of respondents 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. 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.*

5 Research methodology

The research model of this study is shown in Fig. 4. Based on an integration of HCI with TAM, this study predicts the complex and emergency relationship between these constructs and their effect on the grades and GPAs of the students. For this purpose, the researcher moved from the traditional direct effect to more complex non-linear relationships. For analysis, the researcher followed these main statistical procedures: using the percentages to present personal information and technology experiences; conducting independent sample t-test and one-way ANOVA test to outline the statistical differences among participants; and conducting nonlinear regression analysis based on estimated coefficients that will be derived from the best fit curve for the data when using the curve estimation function, this strategy was proposed by (Keum, 2019). Also, ANOVA was used to explore the relationship between constructs (in linear and nonlinear regression analysis). 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.

In this study, two approaches have been integrated during hypothesis validation and data collection. First, it was the qualitative method by reviewing literature and 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 model. Second, the primary data was collected via a survey in order to test the effect of the constructs. The secondary data was collected by extracting the grades from Moodle that was hosted by the Kadir Has University in Turkey, called "Khas Learn system."

Most universities employ online management systems as a platform like Moodle to conduct web-based courses and share their content. Also, Moodle is equipped with tools and applications that support self-assessments via the internet, such as quizzes, exams, and assignments with informative and supportive activities that address students and with discussion boards, social groups, and forums (AL-Sayid

& Kirkil, 2022). According to theories of social constructivist and social constructionist learning, Moodle is a popular platform due to its pedagogical approach in education (González et al., 2010), and is well known in different countries due to its economy and easiness (Nicholas-Omoregbe et al., 2017).

5.1 Developing survey and variables

The researcher used a structured survey to test the hypotheses. He derived quantitative variables related to HCI factors integrated with EoU and U as main predictors for students' attitude toward e-learning actual use (see Table 35 of the supplementary material). Additionally, he included this survey with the demographic and technology usage questions that relate to gender, age, academic years, GPA, devices, and tools used, as well as the time on the internet or on learning online. Furthermore, he measured the data required in this survey via the Five-Likert scale, which ranged from "strongly agree" to "strongly disagree."

Undergraduate students who attended Kadir Has online courses, Probability and Statistics for Engineers (GE204) and Technical Drawing (IE205), were surveyed. "GE204" was designed to cover topics on data presentation and analysis, and concepts of probability. It was taught to 78 students; and this course grading policy was two online midterm exams (40%), five paper assignments (10%), and (5%) for participation. While "IE205" was designed to introduce the fundamental engineering drawing techniques and computer-aided methods, it was taught to 49 students who adapted and installed AutoCAD 2017 software on their laptops to solve weekly online class assignments uploaded through Khas Learn at the end of each lecture; and this course grading policy was online midterm exam (30%), projects (30%), and online final exam (40%). Out of those students, there were 15 students who attended the two courses.

The sampling strategy undertaken in this study consisted of directly surveying 112 full-time undergraduate students from the two courses, which were conducted online at Kadir Has University. The researcher received 103 responses, with a response rate of 92%.

5.2 Test survey validity and reliability

To validate the hypotheses of this study, especially the constructs related to HCI that may affect e-learning acceptance concerning TAM, a semi-structured questionnaire was conducted based on previous studies and expert opinions. Furthermore, twenty experts and students in the university were interviewed, and the results were coded using grounded theory. After that, hypotheses were built and tested by designing a structured survey. Moreover, a group of experts reviewed the survey contents to be sure about its validity. Based on the feedback, the first adjustment was performed. Also, the questionnaire construct's reliability, which is acceptable when the value of Cronbach's alpha remains greater than 0.70 as defined by Cronbach (1951), was proven by a pilot survey distributed to thirty students who had not participated in the analysis process of actual data later collected. The reliability indicators ranged from 0.733 to 0.911, all greater than 0.70 (Table 1). This reveals that the researcher survey

Table 1 Reliability statistic of factors influencing E-learning acceptance and SS

Factor	Variables	Cronbach's Alpha
Usefulness (U)	U1, U2, U3	0.911
Ease to Use (EoU)	EoU1, EoU2, EoU3	0.751
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
Course Evaluations' System (CES)	CES1, CES2, CES3	0.806
Course Structure and Content (CSC)	CSC1, CSC2, CSC3	0.797

construct has internal consistency. As a result, the third variable of course environment (CE3) was excluded from the factor calculation, as it does not exceed the threshold of Cronbach's alpha. Thus, the primary tool of this research is considered reliable.

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

Table 2 Personal information (Survey Part One)

Personal information		Frequency	Percent
Gender	Male	77	74.8%
	Female	26	25.2%
Age	18–20	18	17.5%
	21–25	85	82.5%
Academic Year	2 years	23	22.3%
	3 years	44	42.7%
	4 years or more	36	35.0%
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%
The course registered	GE204	55	53.4%
	IE205	33	32.0%
	GE204 & IE205	15	14.6%
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%

(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 (see Table 2 of the supplementary material).

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 whose sampling adequacy (Sharma & Alvi, 2021) was (KMO = 0.842), and indicated a meritorious level, Bartlett test for sphericity was statistically significant ($\chi^2 = 1613.684$, $p = 0.000$), verifying that correlations between variables were sufficiently large to justify the principal components analysis.

6 Findings and discussion

6.1 Demographic and descriptive statistics

The data analysis results indicate that 74.8% of participants are males; 82.5% are aged under 26 years old; 42.7% have been in the university for three years; 35.9% obtained 2.00 to 2.49 in their GPA, classified under "Fair" (see Table 36 of the supplementary material), and 30.1% obtained 2.50 to 2.99, classified under "Satisfactory"; 53.4% attended the GE204 course; 64.1% expected to get AB or BB grade letter (Table 2), which ranged between 3.5–4.0 and classified under "Very Good to Excellent" (see Table 36 of the supplementary material).

Furthermore, the results show that 87.4% use laptops in their web-based learning; 51.5% use 5 to 8 platforms or tools in their courses web-based; 37.9% spend 4–6 h per day on the internet, and 48.5% study 4–6 h per week in online courses (see Table 4 of the supplementary material).

Table 3 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%
Preferring online to face to face learning	Yes	68	66.0%
	No	25	24.3%
	I do not know	10	9.7%
Course grade as expected	Yes	38	36.9%
	No	65	63.1%
Course grade equal or greater than student's GPA	Greater	61	59.2%
	Equal	25	24.3%
	Less	17	16.5%

To ensure positive outcomes for the e-learning system short questions were prepared, and course grades were calculated. The results show that 82.5% of students considered that the use of Khas Learn made them safe and secure; 66.0% preferred online to face-to-face learning; 36.9% got their expected grades in the courses; and 59.2% got marks greater than their GPA (Table 3).

6.2 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) 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 the coefficient of determination (R^2); values of adjusted coefficient of determination (adjusted R^2) as part of the total variance explained by the model; and values of the standard error of estimate (SEE) 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 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

Table 5 Guidelines from Cohen (1988) for classifying the size of correlation effect

$\lvert r \rvert$	R^2	Size of effect
$0.1 \le \lvert r \rvert < 0.3$	$0.01 \le R^2 < 0.09$	Small
$0.3 \le \lvert r \rvert < 0.5$	$0.09 \le R^2 < 0.25$	Medium
$\lvert r \rvert \ge 0.5$	$R^2 \ge 0.25$	Large

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 5, 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 1 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.

6.2.1 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 a 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 ($\beta = 0.492$, $F = 32.313$, $p < 0.05$); and for non-linear regression R^2 is equal to 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 optimum 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 6), which concludes that the size of a correlation had a "large" effect.

The selected cubic regression function is:

$$U = -7.597 + (8.918 * \text{EoU}) + (-2.51 * \text{EoU} ** 2) + (.241 * \text{EoU} ** 3)$$

Table 6 Model statistics and parameter estimates of the fitted models

Model	Model statistics			Parameter estimates			
	R^2	R^2 (adj)	SEE	b0	b1	b2	b3
Linear	0.242	0.235	0.929	0.831	0.662		
Logarithmic	0.236	0.229	0.933	0.432	2.233		
Inverse	0.218	0.211	0.943	5.216	-6.627		
Quadratic	0.243	0.228	0.933	1.257	0.416	0.034	
Cubic	0.273	0.251	0.919	-7.597	8.918	-2.510	0.241
Compound	0.196	0.188	0.358	1.343	1.249		
Power	0.206	0.198	0.355	1.128	0.779		
S	0.207	0.199	0.355	1.817	-2.412		

6.2.2 Visual design and usefulness or ease of use 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 ($\beta = 0.306$, $F = 10.447$, $p < 0.05$); and for non-linear regression R^2 is equal to 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 optimum 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, $\boldsymbol{H2_{VD}}$ is supported. Also, the obtained value for R^2 of the quadratic model is 0.109 (see Table 9 of the supplementary material), which concludes that the size of a correlation had a "medium" effect.

The selected quadratic regression function is:

$$U = 3.595 + (-.625 * VD) + (.146 * VD ** 2)$$

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 ($\beta = 0.205$, $F = 4.419$, $p < 0.05$); and for non-linear regression R^2 is equal to 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 optimum 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, $\boldsymbol{H3_{VD}}$ is supported. Also, the obtained value for R^2 of the cubic model is 0.076 (see Table 10 of the supplementary material), which concludes that the size of a correlation had a "small" effect.

The cubic regression function selected is:

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

6.2.3 Course environment and usefulness or ease of use 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 ($\beta = 0.438$, $F = 23.995$, $p < 0.05$); and for non-linear regression, R^2 is equal to 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 optimum 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, $\boldsymbol{H2_{CE}}$ is supported. Also, the obtained value for R^2 of the cubic and quadratic models are 0.199 (see Table 11 of the supplementary material), which concludes that the size of a correlation had a "medium" effect.

The selected quadratic and cubic regression functions are, respectively:

$$U = -.982 + (1.700 * CE) + (-.137 * CE ** 2)$$
$$U = 2.072 + (-.926 * CE) + (.589 * CE ** 2) + (-.065 * CE ** 3)$$

The effect of course environment 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 ($\beta=0.431$, $F=23.001$, $p<0.05$); and for non-linear regression R^2 is equal to 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 optimum 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, $\boldsymbol{H3_{CE}}$ is supported. Also, the obtained value for R^2 of the cubic model is 0.187 (see Table 12 of the supplementary material), which concludes that the size of a correlation had a "medium" effect.

The selected cubic regression function is:

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

6.2.4 Content quality and usefulness or ease of use 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 ($\beta=0.339$, $F=13.151$, $p<0.05$); and for non-linear regression R^2 is equal to 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 optimum 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 (see Table 13 of the supplementary material), which concludes that the size of a correlation had a "medium" effect.

The selected linear regression function is:

$$U = 1.263 + (.558 * CQ)$$

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 ($\beta=0.408$, $F=20.171$, $p<0.05$); and for non-linear regression R^2 is equal to 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 optimum 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 (see Table 14 of the supplementary material), which concludes that the size of a correlation had a "medium" effect.

The selected linear regression function is:

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

6.2.5 System quality and usefulness or ease of use 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 ($\beta = 0.496$, $F = 32.918$, $p < 0.05$); and for non-linear regression R^2 is equal to 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 optimum 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, $\boldsymbol{H2_{SQ}}$ is supported. Also, the obtained value for R^2 of the quadratic model is 0.267 (see Table 15 of the supplementary material), which concludes that the size of a correlation had a "large" effect.

The selected quadratic regression function is:

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

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 ($\beta = 0.307$, $F = 10.544$, $p < 0.05$); and for non-linear regression R^2 is equal to 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 optimum 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, $\boldsymbol{H3_{SQ}}$ is supported. Also, the obtained value for R^2 of the quadratic model is 0.167 (see Table 16 of the supplementary material), which concludes that the size of a correlation had a "medium" effect.

The selected quadratic regression function is:

$$\mathrm{EoU} = 5.484 + (-1.354 * \mathrm{SQ}) + (.246 * \mathrm{SQ} ** 2)$$

6.2.6 Learner-interface interactivity and usefulness or ease of use 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 ($\beta = 0.365$, $F = 15.519$, $p < 0.05$); and for non-linear regression R^2 is equal to 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 optimum 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 (see Table 17 of the supplementary material), which concludes that the size of a correlation had a "medium" effect.

The selected S-curve regression function is:

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

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 ($\beta = 0.393$, $F = 18.444$, $p < 0.05$); and for non-linear regression R^2 is equal to 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 optimum 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, $\boldsymbol{H5_{LInt}}$ is supported. Also, the obtained value for R^2 of the cubic model is 0.185 (see Table 18 of the supplementary material), which concludes that the size of a correlation had a "medium" effect.

The selected cubic regression function is:

$$\text{EoU} = 7.718 + (-5.501 * \text{LInt}) + (1.891 * \text{LInt} ** 2) + (-.186 * \text{LInt} ** 3)$$

6.2.7 Navigation results and usefulness or ease of use 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 ($\beta = 0.438$, $F = 24.019$, $p < 0.05$); and for non-linear regression R^2 is equal to 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 optimum 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, $\boldsymbol{H4_{Nav}}$ is supported. Also, the obtained value for R^2 of the S-curve model is 0.216 (see Table 19 of the supplementary material), which concludes that the size of a correlation had a "medium" effect.

The selected S-curve regression function is:

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

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 ($\beta = 0.513$, $F = 36.154$, $p < 0.05$); and for non-linear regression R^2 is equal to 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 optimum result than a non-linear relationship since higher R^2_{adj}, lower SEE, and slight difference R^2 values indicate a better function. So, $\boldsymbol{H5_{Nav}}$ is not supported. Also, the obtained value for R^2 of the linear model is 0.264 (see Table 20 of the supplementary material), which concludes that the size of a correlation had a "large" effect.

The selected linear regression function is:

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

6.2.8 Course evaluation's system and usefulness or ease of use 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 ($\beta = 0.498$, $F = 33.339$, $p < 0.05$); and for non-linear regression R^2 is equal to 0.259 and 0.250, R^2_{adj} is equal to 0.236 and 0.243, and SEE is equal to 0.928 and 0.924 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 optimum 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, $\boldsymbol{H4_{CES}}$ is supported. Also, the obtained value for R^2 of the logarithmic model is 0.250 (see Table 21 of the supplementary material), which concludes that the size of a correlation had a "large" effect.

The selected logarithmic regression function is:

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

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 ($\beta = 0.431$, $F = 23.001$, $p < 0.05$); and for non-linear regression R^2 is equal to 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 optimum 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, $\boldsymbol{H5_{CES}}$ is supported. Also, the obtained value for R^2 of the cubic model is 0.315 (see Table 22 of the supplementary material), which concludes that the size of a correlation had a "large" effect.

The selected cubic regression function is:

$$\text{EoU} = -.713 + (3.663 * \text{CES}) + (-1.064 * \text{CES} ** 2) + (.110 * \text{CES} ** 3)$$

6.2.9 Course structure and content and usefulness or ease of use 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 ($\beta = 0.418$, $F = 21.416$, $p < 0.05$); and for non-linear regression R^2 is equal to 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 optimum 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, $\boldsymbol{H4_{CSC}}$

is supported. Also, the obtained value for R^2 of the S-curve model is 0.215 (see Table 23 of the supplementary material), which concludes that the size of a correlation had a "medium" effect.

The selected S-curve regression function is:

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

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 ($\beta = 0.492$, $F = 32.314$, $p < 0.05$); and for non-linear regression R^2 is equal to 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 optimum 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, $\boldsymbol{H5_{CSC}}$ is supported. Also, the obtained value for R^2 of the quadratic model is 0.270 (see Table 24 of the supplementary material), which concludes that the size of a correlation had a "large" effect.

The selected quadratic regression function is:

$$EoU = 4.723 + (-1.060 * CSC) + (.209 * CSC ** 2)$$

6.2.10 Human computer interaction and students' academic outcomes 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 to 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 optimum result than other non-linear relationship since higher R^2 and R^2_{adj} and lower SEE values indicate a better function. So, $\boldsymbol{H8_{LInt,\ GPA}}$ is supported. Also, the obtained value for R^2 of the S-curve model is 0.071 (see Table 25 of the supplementary material), which concludes that the size of a correlation had a "small" effect.

The selected S-curve regression function is:

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

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 to 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 optimum result than other non-linear relationship since higher R^2 and R^2_{adj} and lower SEE values indicate a better function. So, $\boldsymbol{H8_{LInt,\ Grades}}$ is supported.

Also, the obtained value for R^2 of the cubic curve model is 0.158 (see Table 26 of the supplementary material), which concludes that the size of a correlation had a "medium" effect.

The selected cubic regression function is:

$$\text{Grades} = 69.043 + (-48.674 * \text{LInt}) + (21.713 * \text{LInt} ** 2) + (-2.367 * \text{LInt} ** 3)$$

6.2.11 Usefulness or ease of use and students' academic outcomes 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 to 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 optimum result than other non-linear relationship since higher R^2 and R^2_{adj} and lower SEE

Table 7 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	0.273	Large	0.522	0.000	Yes
H2	VD → U	Quadratic	0.109	Medium	0.330	0.003	Yes
	CE → U	Cubic or Quadratic	0.199	Medium	0.446	0.000	Yes
	CQ → U	Linear	0.115	Medium	0.339	0.000	No
	SQ → U	Quadratic	0.267	Large	0.517	0.000	Yes
H3	VD → EoU	Cubic	0.076	Small	0.276	0.049	Yes
	CE → EoU	Cubic	0.187	Medium	0.432	0.000	Yes
	CQ → EoU	Linear	0.166	Medium	0.407	0.000	No
	SQ → EoU	Quadratic	0.167	Medium	0.409	0.000	Yes
H4	LInt → U	S-curve	0.187	Medium	0.432	0.000	Yes
	Nav → U	S-curve	0.216	Medium	0.465	0.000	Yes
	CES → U	Logarithmic	0.250	Large	0.500	0.000	Yes
	CSC → U	S-curve	0.215	Medium	0.464	0.000	Yes
H5	LInt → EoU	Cubic	0.185	Medium	0.430	0.000	Yes
	Nav → EoU	Linear	0.264	Large	0.514	0.000	No
	CES → EoU	Cubic	0.315	Large	0.561	0.000	Yes
	CSC → EoU	Quadratic	0.185	Medium	0.430	0.000	Yes
H8	LInt → GPA	S-curve	0.071	Small	0.266	0.007	Partially
	LInt → Grade	Cubic	0.158	Medium	0.397	0.001	Partially
H9	U → GPA	Cubic	0.085	Small	0.292	0.032	Partially

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

values indicate a better function. So, $\boldsymbol{H9}_{U,\ Grades}$ is supported. Also, the obtained value for R^2 of the cubic curve model is 0.085 (see Table 27 of the supplementary material), which concludes that the size of a correlation had a "small" effect.

The selected cubic regression function is:

$$\text{Grades} = 6.352 + (56.169 * \text{U}) + (-15.228 * \text{U} ** 2) + (1.270 * \text{U} ** 3)$$

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 7 where perceived CES is the strongest determinant in the model.

6.3 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 (Fig. 5).

For a complete explanation of the nonlinearity compared with linear relationships, the graphic presentations (Figs. 6, 7 and 8, Fig. 9 of the supplementary

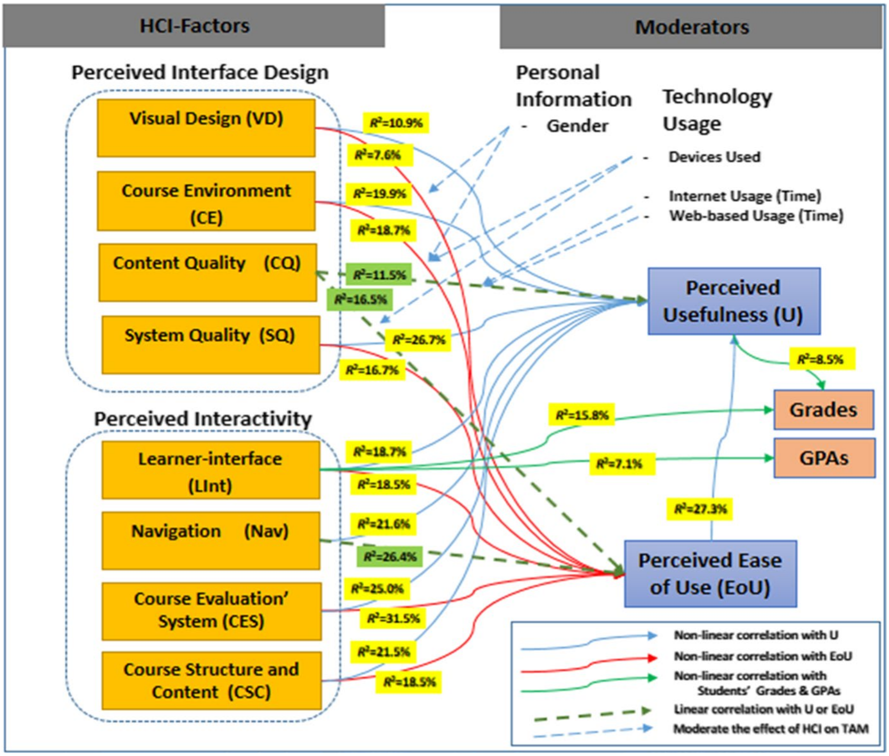


Fig. 5 The researcher's conceptual model

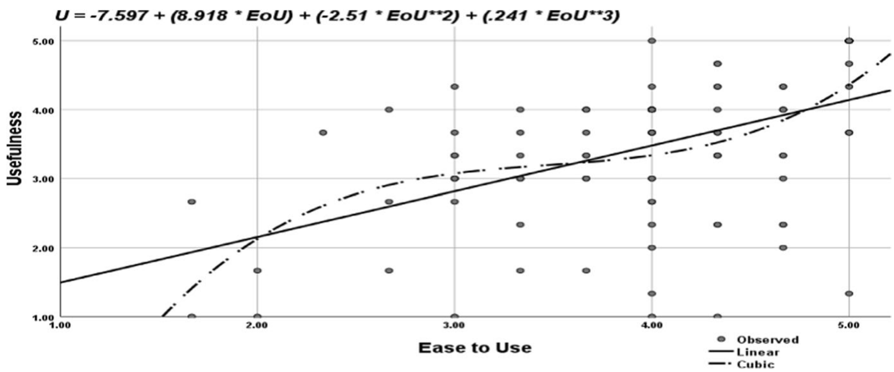


Fig. 6 Linear and non linear correlation model for the variables: EoU and U, (**a**) linear and cubic relations EoU, U

material, Figs. 9, 10 and 11) are useful to figure out the pattern of changes in the resulting attribute, based on changes in the outcomes' values. They are calculated

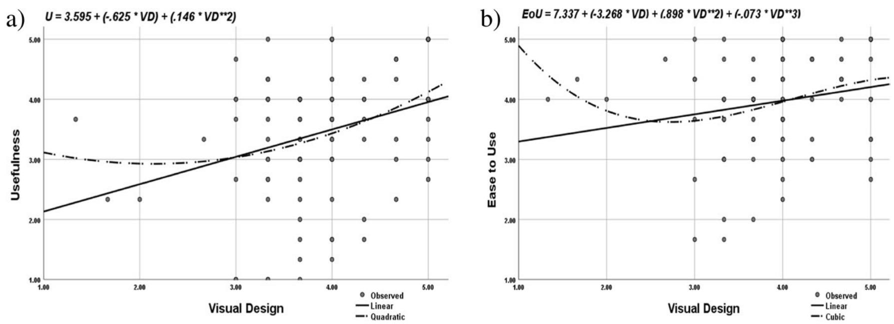


Fig. 7 Linearity and non-linearity correlation models for the variables: EoU, U and VD, (**a**) linear and quadratic relations VD, U, (**b**) linear and cubic relations VD, EoU

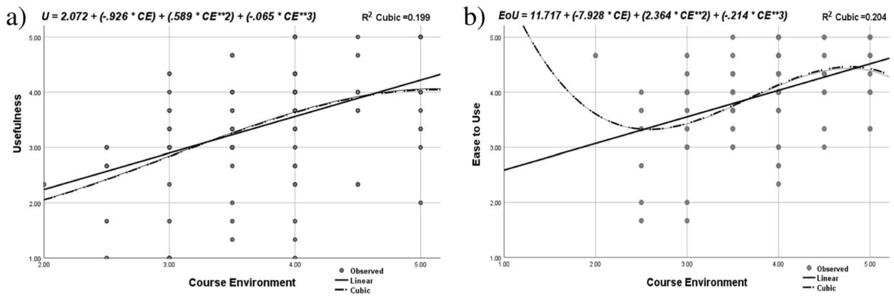


Fig. 8 Linearity and non-linearity correlation models for the variables: EoU, U and CE, (**a**) linear and cubic relations CE, U, (**b**) linear and cubic relations CE, EoU

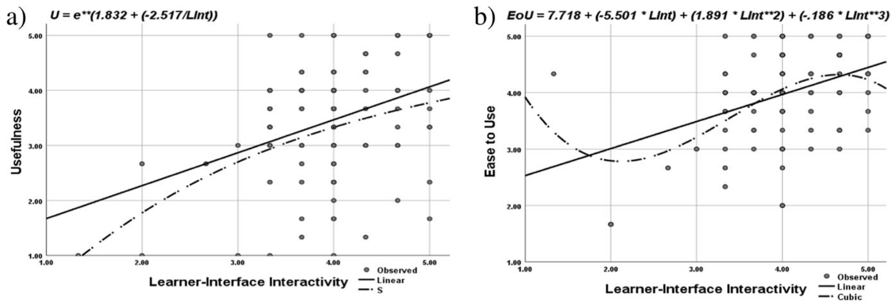


Fig. 9 Linearity and non-linearity correlation models for the variables: EoU, U and LInt, (**a**) linear and S-curve relations LInt, U, (**b**) linear and cubic relations LInt, EoU

after substitution in modelled equations with threshold values that are associated with predictors and multiplied by coefficients in each case.

The scatter plots (see Fig. 6, and see Fig. 12b of the supplementary material) present the linear and cubic relations in the regression models for the factors EoU → U and CES → U. On the left part, the curve of non-linearity is oriented as a positive trend

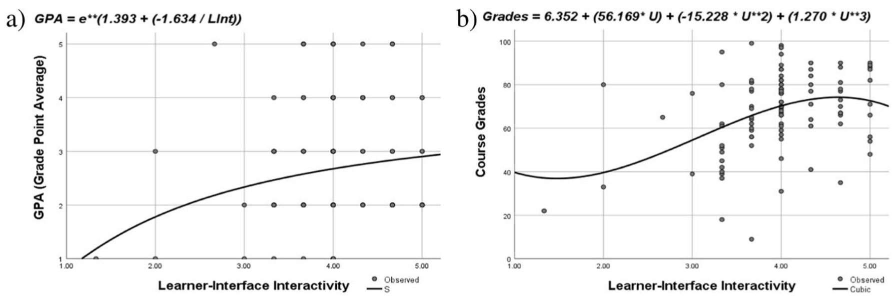
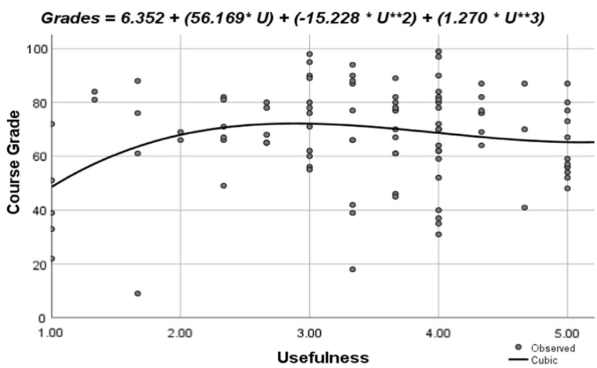


Fig. 10 Non-linearity correlation models for the variables: GPAs, Grades and LInt, (**a**) S-curve relations LInt, GPAs, (**b**) cubic relations LInt, Grades

Fig. 11 Non-linearity correlation models for the variables: U and Grades, (**a**) cubic relations U, Grades



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 way of getting information from Khas Learn, comprehending provided information by the system, no trouble in using Khas Learn in performing tasks, or about the goodness of online self-assessment tools provided by the Khas Learn. Furthermore, the path coefficient size for the two models of EoU → U ($\beta_{\text{linear}} = 0.492$, $\beta_{\text{nonlinear}} = 0.522$) is slightly higher than the average ($\beta_{\text{avg.}} = 0.400$), according to the study of Šumak et al. (2011).

Furthermore, scatter plots (see Fig. 7a, and see Fig. 9a, Fig. 9b, and Fig. 13b of the supplementary material) present the linear and quadratic relations in the regression models for the factors VD → U, SQ → U, SQ → EoU, and CSC → EoU respectively. On the left part, the curve of non-linearity is oriented neutrally or negatively and paralleled with the abscission or the downward curvature appears sharply at the center, while there is a positive trend paralleled with linearity from the middle toward the upper right quadrant. The gap is obvious between the linearity or nonlinearity models considering the enhancement in the students' perceptions who disagree or strongly disagree with the readability and consistency of text, colors, layout, and the attractiveness of the system design; or with the Khas Learn being fun to operate, satisfactory in its functions, or it is course materials to be accessible without much effort. Furthermore, The gap widens between the two models since the higher the student's perceived SQ or CSC who moved from strongly disagree to neutrality, the lower their perceived 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. This indicates that this group of students may not be affected by any effort in improving VD, SQ, or CSC as a prerequisite to improving their perception of U or EoU. This was not answered by linearity. Moreover, the path coefficient size for the two models of SQ → U ($\beta_{\text{linear}} = 0.496$, $\beta_{\text{nonlinear}} = 0.517$), which is higher than the average according to the study of Šumak et al. (2011) where ($\beta_{\text{avg.}} = 0.330$). And the path coefficient size for the two models of SQ → EoU ($\beta_{\text{linear}} = 0.307$, $\beta_{\text{nonlinear}} = 0.409$) in which nonlinearity path coefficient size is higher than the average, according to the study of Šumak et al. (2011) where ($\beta_{\text{avg.}} = 0.300$).

Whereas, the scatter plots (see Figs. 7b, 8b, or 9b) present the linear and cubic relations in the regression models for the factors VD → EoU, CE → EoU, and LInt → EoU. On the left part, the curve of non-linearity is oriented negatively. The gap widens between the linearity and nonlinearity models, since the higher the student's perceived VD, CE, or LInt who moved from strongly disagree to neutrality, the lower they perceived 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; the extent of the course webpage was 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; or the extent to which the 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, 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.

Figure 8a 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.

The scatter plots (see Fig. 9a, and see Fig. 11a, and Fig. 13a of the supplementary material) present linear and S-curve relations for the factors LInt → U, Nav → U, and CSC → U respectively. 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 their 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; also 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. These relations thus similar to the shape of the linear and nonlinear relationship between CE and U, but with less variance. Figure 11b of the supplementary material presents the scatter plot of linear relation for the factors Nav and EoU.

Figure 12a of the supplementary material presents the scatter plot of linear and logarithmic relations for the factors CES and U. On the left part, the curve of nonlinearity 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.

Moreover, Fig. 10a 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 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. Whereas, Fig. 10b 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 negatively 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%, 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 11 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 improvement in students' performance. Where the U-shape was observed but is flattened in the middle, it shows 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.

6.3.1 Moderation results

The moderation test (Table 8) through the macro-PROCESS for SPSS provided by Hayes and Scharkow (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 result shows that gender moderates only the relationship between VD and EOU (b = -0.673, $R^2 = 0.112$, $p < 0.01$); and between CE and EoU (b = -0.607, $R^2 = 0.270$, $p < 0.01$) where b represents the coefficients of the moderation model. Also, it indicates that the effect of VD or CE on EOU is stronger for males ($R^2 = 0.095$, $R^2 = 0.255$, respectively). So, the $\boldsymbol{H6_{gender}}$ is partially supported.

Besides, the test (Table 8) shows that using SMART phones to connect to Khas Learn moderates only the relationship between CQ and EoU (b = 0.490, $R^2 = 0.205$, $p < 0.01$), and between CE and EoU (b = -0.417, $R^2 = 0.219$, $p < 0.01$). It indicates that the effect of CQ on the EoU is stronger for SMART phone usage ($R^2 = 0.389$), while the effect of CE on the EoU is stronger for not using a desktop

Table 8 Hypotheses testing results (Moderation Tests)

Hypoth	Regression	X + M → Y	Int-I X*M	Strong Effect	Support
H6	Gender moderate	*p-value*	*R^2 change* *b = Effect*		Yes Partially
	VD → EoU	$R^2 = 0.112$, $p < 0.05$	$R^2 = 0.060$, $b = -0.673^*$, $p < 0.05$	Male $R^2 = 0.095$	
	CE → EoU	$R^2 = 0.230$, $p < 0.05$	$R^2 = 0.041$, $b = -0.605^*$, $p < 0.05$	Male $R^2 = 0.255$	
H7	SMART Phone use moderate CQ → EoU	$R^2 = 0.205$, $p < 0.05$	$R^2 = 0.038$, $b = 0.490^*$, $p < 0.05$	Yes $R^2 = 0.398$	Yes Partially
	Desktop use moderate CQ → U	$R^2 = 0.219$, $p < 0.05$	$R^2 = 0.032$, $b = -0.417^*$, $p < 0.05$	No $R^2 = 0.276$	
	Daily on internet moderate CQ → U	$R^2 = 0.159$, $p < 0.05$	$R^2 = 0.039$, $b = -0.390^*$, $p < 0.05$	1–3 h $R^2 = 0.319$ 72.8% < 2.53	
	Weekly online study moderate CQ → U	$R^2 = 0.414$, $p < 0.05$	$R^2 = 0.054$, $b = -0.417^*$, $p < 0.05$	1–2 h $R^2 = 0.318$ 68.9% < 2.76	

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

($R^2 = 0.276$). So, the ***H7**$_{SMART}$* and ***H7**$_{Desktop}$* are partially supported. Moreover, the daily time student spends on the internet studying moderates only the relationship between CQ and U (b = -0.390, $R^2 = 0.159$, $p < 0.01$), (b = -0.417, $R^2 = 0.414$, $p < 0.01$). It indicates that the effect of CQ on the U is stronger for 1–3 h. daily using the internet ($R^2 = 0.319$), while it is stronger for 1–2 h. weekly online studying ($R^2 = 0.318$). So, the ***H7**$_{Time}$* is partially supported.

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.

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 Fig. 12a and b, the male group has a steep linear slope in an increasingly

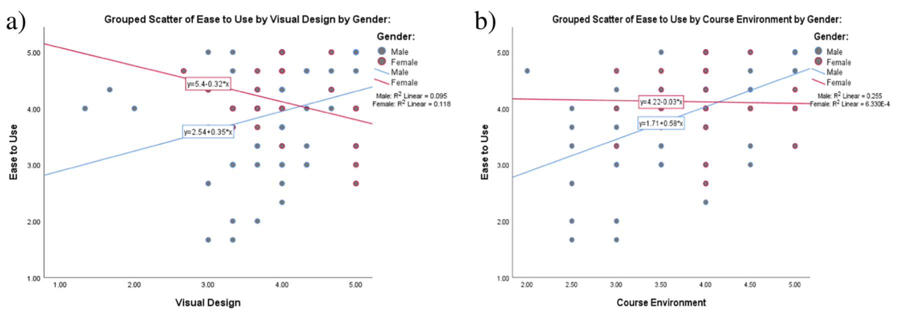


Fig. 12 Interaction plot (Gnender as a Moderator), (**a**) gender moderate relation VD, EoU, (**b**) gender moderate relation CE, EoU

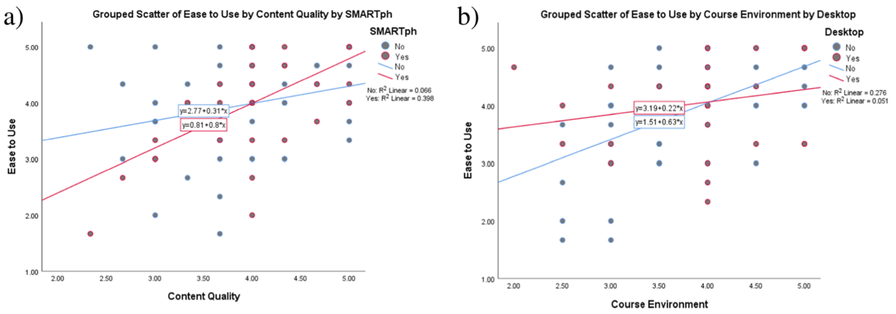


Fig. 13 Interaction plot (technology Usage as a Moderator), (**a**) SMART phone usage moderate relation CQ, EoU, (**b**) desktop usage moderate relation CE, EoU

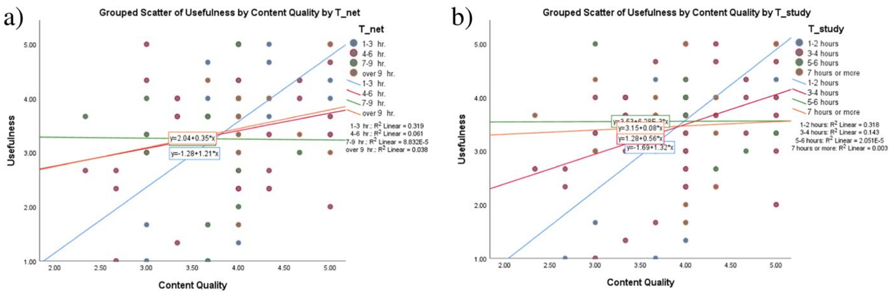


Fig. 14 Interaction plot (time as a moderator), (**a**) time moderate relation CQ, U, (**b**) time moderate relation CQ, EoU

positive direction. The females' group has a steep linear slope in decreasing a negative trend, which shows that males have an enhancing effect for perceived ease of use and visual design link in contrast to females.

In Fig. 13a, 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. In Fig. 13b, 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.

In Fig. 14a and b, 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.

6.4 Statistical differences among participants

To understand the differences across various student groups, based on their age or courses they were registered to, as classified into two layers, the researcher applied

Table 9 Statistical differences according to age (t-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

the independent sample *t*-test method at 0.05 level of significance. The analysis (Table 9) shows that the students aged between 21–25 years old were more likely to rate SQ ($d = 0.67$, Mean = 3.71, $p < 0.05$) than those aged between 18–20, where the effect size (d) of older students is ranked medium.

Besides, the results (Table 10) show that the students registered in the course IE205 are more likely to rate U ($d = 0.52$, Mean = 3.22, $p < 0.05$), LInt ($d = 0.60$, Mean = 4.16, $p < 0.05$), Nav ($d = 0.60$, Mean = 4.18, $p < 0.05$), CES ($d = 0.45$, Mean = 3.97, $p < 0.05$), and CE ($d = 0.55$, Mean = 4.08, $p < 0.05$) than those who registered in the course GE204, where the effect size of the course IE205 is ranked medium.

Furthermore, the data were classified into more than two intervals tested by one-way ANOVA to check the statistical differences among participants. Then, the post hoc tests (LSD) method was employed to detect a statistically significant difference. The analysis shows that the differences among student groups, concerning their academic years and grade expectation, were $P < 0.05$ (see Table 32 of the supplementary material).

Students who are in the 4th or higher academic year or the 2nd or less (see Table 33 of the supplementary material) are more likely to rate CE ($\eta^2 = 0.064$; mean equal to 3.97, 4.00; $p < 0.05$) than who are in the 3rd academic year. The students who are in the 4th or higher academic year are more likely to rate U than those who are in the 3rd or 2nd academic year ($\eta^2 = 0.063$, mean equal to 3.81, $p < 0.05$). Where η^2 = eta-square, it represents the effect size that equals the percentage of the total variance accounted by the treatment effect.

Students whose course grade expectations are "greater" or "equal" (see Table 34 of the supplementary material) are more likely to rate U ($\eta^2 = 0.069$; mean equal to 4.00, 4.04; $p < 0.05$), VD ($\eta^2 = 0.101$; mean equal to 3.91, 3.96; $p < 0.05$), CQ ($\eta^2 = 0.097$; mean equal to 3.88, 3.92; $p < 0.05$), CSC ($\eta^2 = 0.083$; mean equal to

Table 10 Statistical differences according to course (t-Test for Equality of Means)

Factor	t	df	Sig.	Mean		Mean Diff.	Effect size	Effect
				GE	IE		Cohen's *d*	Type
U	-2.340	86	0.022	3.22	3.77	-0.54	0.52	Medium
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

4.14, 4.08; $p<0.05$), and CES ($\eta^2=0.124$; mean equal to 3.81, 4.03; $p<0.05$) than whose course grade expectations are "lower."

7 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 acceptance.

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).

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). 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. As shown in the graphics (Figs. 6, 7 and 8, Fig. 9 of the supplementary material, Figs. 9, 10 and 11), most of the nonlinear relationships between the factors appeared in the form of a U-shaped curve or inverted U-shaped curve which is consistent with the Hakami (2018) clue. Hence proved that 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 an 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). 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).

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).

Moreover, Fig. 12a and b imply 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 past studies (Al-Aulamie, 2013; Binyamin et al., 2020; Goswami & Dutta, 2016; Shaouf & Altaqqi, 2018), 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 Figs. 7b and 8b, which decreases sharply in 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 Figs. 7b and 8b, which decreases sharply in the group that is less satisfied with the perceived VD or CE, which is the female category.

Figure 13a 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. While, Fig. 13b 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 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 14a and b imply 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.

8 Conclusion

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. So, this study sheds light on the effect of HCI factors on TAM main factors. 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 at 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.

8.1 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 educational institutions. From a societal 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. Furthermore, 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 affects 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".

9 Limitations and future works

This study succeeded in exploring the non-linearity relationships between HCI factors and EoU and U of e-learning from the viewpoint of Kadir Has university students whose grades were accessible to the researcher, but the limitations are more likely to generalize the outputs on all other institutions in different sectors, all other users or students in different levels or countries, and some of the other factors which could be investigated in terms of non-linearity.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10639-023-11635-6.

Data availability The datasets generated during and/or analysed during the current study are available from the authors on reasonable request.

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