Learner Differences in Perceived Satisfaction of an Online Learning: an Extension to the Technology Acceptance Model in an Arabic Sample

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Abstract: Online learning constitutes the most popular distance-learning method, with flexibility, accessibility, visibility, manageability and availability as its core features. However, current research indicates that its efficacy is not consistent across all learners. This study aimed to modify and extend the factors of the Technology Acceptance Model (TAM) to examine perceived satisfaction of an Arabic sample in online learning. The integrated factors in the modified model includes: deep level (learning styles), surface level (gender), and cognitive (online self-efficacy) factors. Learning styles were chosen as a central factor. Hence, the online course was purposefully developed to support one pole in each dimension of Felder and Silverman Learning Styles Model (FSLSM) in order to reveal the pedagogical implications of learning styles on learner satisfaction. A total of 70 learners participated voluntarily in the research. At the end of the online course, they were requested to fill in two questionnaires: the Index of Learning Styles (ILS) and a standard questionnaire. The psychometric properties of the latter were firstly analysed to validate the instrument. Then, Partial Least Squares Structural Equation Modelling (PLS-SEM) was conducted to examine the proposed hypotheses. The model achieves an acceptable fit and explains 44.8% of variance. Perceived usefulness represented the best predictor, whereas online self-efficacy and perceived ease of use failed to show a direct impact on perceived satisfaction. Furthermore, neither learning styles nor gender diversity had direct influence on the dependent factors. Accordingly, the research suggested that other variables may have to be integrated to enhance the power of the model.

Keywords: online learning, learning styles, gender diversity, online self-efficacy, learner satisfaction, Technology Acceptance Model (TAM)

1 Introduction

The rapid development of digital technologies, and most prominently, e-learning, has revolutionised the methods of distance learning. In this vein, a definition of e-learning must first be established and perhaps the most widely-accepted definition is "the delivery of learning with the assistance of interactive, electronic technology, whether offline or online" as cited in Procter (2003). It is noteworthy that 'e-learning' and 'online learning' are not synonymous terminologies. For the purposes of this research, 'e-learning' is used as a general concept encompassing online learning as well.

Although the flexibility, accessibility, visibility, manageability, and availability of e-learning systems have helped to address some of the limitations of traditional learning, this does not mean that traditional methods are to be altogether replaced yet. The examination of e-learners responses to their online learning experience can shed some light on why this is so. According to Bouhnik & Marcus (2006), some common expressions of dissatisfaction are connected with the absence of a 'learning atmosphere', and the lack of direct, for example, face-to-face interaction between 'learner-learner' and 'learner-instructor'. They also stated that in online learning settings, students believe that they do not get enough detail in response to their enquiries, and the needed time to learn a new topic is longer, when compared with apprehending a new topic in a traditional way.

Other personal and environmental factors that may lead to user dissatisfaction entail the absence of 'self-motivation', the difficulty of constructing new knowledge without direct guidance, and the lack of self-efficacy in the use of e-learning (Bouhnik & Marcus, 2006; Dutton, Dutton, & Perry, 2001). Such drawbacks are indicative of the reasons why some users withdraw from their online courses after their first experience or failure to pass it. Thus, in order to accept the conclusion of Sun, Tsai, Finger, Chen, & Yeh (2008) that e-learning is an alternative method to traditional learning, such issues have to be tackled.

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Many models were proposed to examine factors that can help towards the prediction of user intention to accept technologies, or perceived satisfaction, for instance, the Theory of Planned Behaviour (TPB) (Ajzen, 1991), the Consumer Acceptance of Technology (CAT) model (Kulviwat, Bruner, Kumar, & Clark, 2007), the Integrated Conceptual Model (ICM) (Sun et al., 2008), and the Technology Acceptance Model (TAM) (Davis, 1986). According to literature, TAM represents one of the most commonly used models (Bogozzi, 2007; Tarhini, Hassouna, & Abbasi, 2015; Sun et al., 2008). Although it has been widely adopted, few studies have investigated its reliability and validity in developing countries (Tarhini et al., 2015; Teo, 2008). Furthermore, the model was designed for use with a general variety of technologies, and not a particular one.

In Iraq, the Higher Education system is considered the best in the Middle East and, more specifically, in the Arab Gulf region (Kaghed & Dezaye, 2009). However, it was isolated from the environment of scientific research due to the regime of Saddam Hussein and the sanctions imposed by the United Nations (Kaghed & Dezaye, 2009). Until the middle of 2003, Iraqi people did not have access to the internet because its public usage was forbidden by the authorities. After the second Gulf war, the Ministry of Higher Education and Scientific Research (MHESR-I) took serious steps to reconstruct Higher Education albeit in pertinence to the traditional education only; attempts for the adoption of e-learning have been limited. Many reasons can be accounted for this and the prevention of widespread use of online learning in Iraq such as the low internet bandwidth even in public educational institutions; the lack of experience of the internet and web-based learning; poverty and low income. Hence, the present study attempted to examine learner perspectives on this new experience in order to promote quality in learning. In this context, this is unexplored area of research. Learning styles as a psychological factor were integrated in the course design as a core variable that may affect learner perceptions. Although more than 71 learning style models were proposed (Coffield, Moseley, Hall, & Ecclestone, 2004), the FSLSM (Felder & Silverman, 1988) was adopted in this research for several reasons. Firstly, it is the most dominant model in previous studies (Akbulut & Cardak, 2012; Al-Azawei & Badii, 2014). Moreover, it is suitable for Technology Enhanced Learning (TEL) (Graf, 2007; Viola, Graf, & Leo, 2006). Finally, the proposed instrument to diagnose this model was validated (Felder & Brent, 2005; Litzinger, Lee, Wise, & Felder, 2007; Zywno, 2003).

This research aimed to achieve two goals. First, it modified TAM in order to assess perceived satisfaction in online learning instead of attitude to use a technology by incorporating three individual variables of learners: deep level factor (learning styles), surface level factor (gender diversity), and cognitive factor (online self-efficacy). The central factor in this modification was learning styles because studies have not provided conclusive evidence either for or against their pedagogical impacts on perceived satisfaction, or whether mismatching teaching and learning styles can lead to learner dissatisfaction. Accordingly, the investigated learning environment was designed to serve one pole in each dimension of the FSLSM. Second, the study examined the soundness of the modified version of TAM in a developing country in order to contribute to the existing evidence regarding the appropriateness of the model in such learning environment. The rest of the research is structured as follows. In Section 2, the basic concepts are discussed. Section 3 identifies the main factors of the proposed model and hypotheses. Section 4 depicts the adopted methodology. The main findings are presented and discussed in Section 5. Subsequently, Section 6 highlights the implications and limitations of the research. Finally, Section 7 encapsulates the main themes of the study and the possible future work.

2 Basic Concepts

2.1 Online learning

Online learning has been classified into two categories: synchronous and asynchronous. In the former, learners and instructors are geographically separated, but work simultaneously; in the latter, learners and instructors are both geographically and timely separated. In this research, asynchronous category was adopted because it gives learners more flexibility to reflect on the course content and the issue of time zone was addressed. According to Solimeno, Mebane, Tomai, & Francescato (2008), online learning is very suitable for people who have problems of time-management or job-commitment nature. However, the benefits of online learning are subject to other variables of learners, teachers, and learning environments. Accordingly, the reasons underlying learner dissatisfaction have not been investigated out of these dimensions.

On the other hand, the core drawback in an asynchronous learning environment is the absence of direct face-to-face interaction. Sweeney, Ingram, & Swee (2001) compared face-to-face, synchronous, and asynchronous learning modes. From learners' perspective, traditional tutorials were more preferable, effective, helpful, and satisfying, whereas chat room in synchronous tutorials was more enjoyable. Furthermore, whilst ethnicity showed to affect learner perception of type of tutorial, gender and internet experience did not. Generally, all participants preferred face-to-face learning over the other two types.

2.2 The Technology Acceptance Model (TAM)

Davis (1986) proposed the Technology Acceptance Model (TAM) to predict the tendency of users to accept technologies. The model was originally developed to explain the behaviour of users towards computer-usage and Information Technology (IT). The main variables in this model are perceived usefulness (PU) and perceived ease of use (PEOU) which can influence users' attitudes towards using a technology (ATU). This model is widely employed in order to assess the acceptance of a particular technology (Bogozzi, 2007; Tarhini et al., 2015). Investigating the integrated factors exhibited how they perfectly linked with user attitude and behavioural intention. Therefore, studies have adopted the model to reveal the acceptance of users towards, for example, e-mail, computer based learning, blended learning, Rich Site Summaries (RSS), and online learning (Gefen & Straub, 1997; Ong & Lai, 2006; Liu, Chen, Sun, Wible, & Kuo, 2010; Tarhini et al., 2015).

On the other hand, perceived usefulness and ease of use factors affecting learner satisfaction, appeared to be the most important parameters in studies aiming to find the causal relationship among different variables and perceived satisfaction (Arbaugh, 2000; Atkinson & Kydd, 1997; Drennan, Kennedy, Pisarski, & Taylor, 2011; Liaw, 2008; Sun et al., 2008). In theory, there is an axiomatic relationship among perceived usefulness, ease of use and satisfaction because compounding increased expectation of outcome improvement with less effort leads to higher level of satisfaction. Consequently, based on the positive results of literature such as these in Liaw (2008) and Sun et al. (2008), we investigated the causal link among these factors and learner satisfaction as the first change in the original TAM.

3 Theoretical Framework and Hypotheses

Although many factors can be incorporated to infer learner satisfaction, the notion that 'simpler is better' was adopted. Therefore, only learner characteristics were used to modify and extend TAM, so as to illustrate the role of such features, more specifically, learning styles. Davis (1986) examined the effect of perceived usefulness (PU) and ease of use (PEOU) with the intention to adopt a technology. The expectation that a particular technology would not assist to enhance performance or it require high mental effort may lead to users' dissatisfaction. As such, we examined the value of PU and PEOU on perceived satisfaction (PS). However, individual differences should be considered because such features and psychological traits may affect learner satisfaction in online learning. Additionally, prior literature that used TAM as a research framework indicated the importance of extending the model to improve its power (Edmunds, Thorpe, & Conole, 2012; Legris, Ingham, & Collerette, 2003; Venkatesh & Davis, 2000); hence, another change in the TAM includes integrating learning styles (deep level factor), gender diversity (surface level factor), and online self-efficacy (OSE) (cognitive factor). Figure 1 depicts the proposed dimensions of the model.

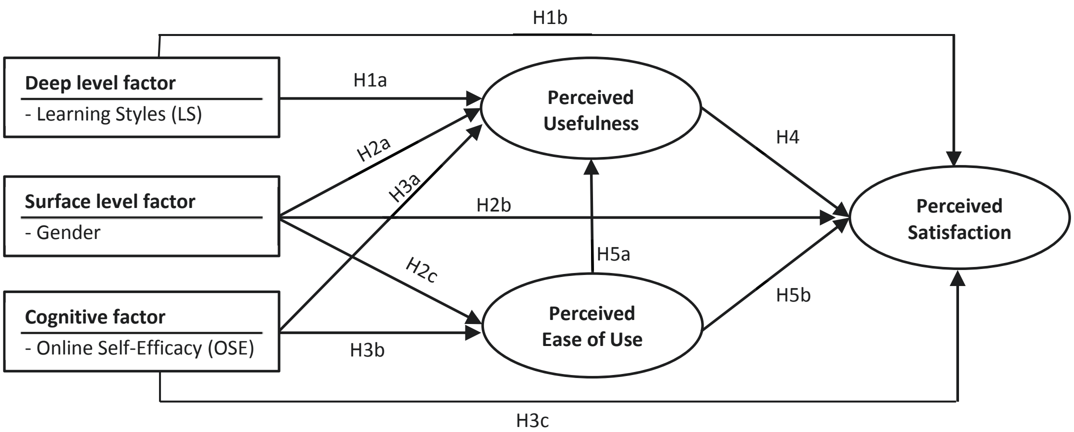

Figure 1: The proposed model

3.1 Deep level factor (Learning styles)

Learning styles represent the main extension of this study as a deep level factor, with potential influences on perceived usefulness and satisfaction. Felder (1996) defined learning styles as the "characteristic strengths and preferences in the ways they 'learners' take in and process information". The hypothesis of learning styles suggests the importance of matching learning and teaching styles because this trait affects academic achievement, learning time, learning patterns and learner satisfaction (Brown, 2007; Graf, 2007; Klašnja-Milićević, Vesin, Ivanović, & Budimac, 2011; Popescu, 2010). Additionally, as Felder & Brent (2005) stated, neglecting learning styles results in learners to withdrawing from a course or underperforming. Respectively, there seems to be a correlation among these factors as learners will not accept a learning environment if their preferences are ignored. Based on this assumption, perceived usefulness and satisfaction regarding a particular learning technology may rely on the level of accommodating their styles. Contrary, some researchers have disputed the pedagogical implications of learning styles due to the absence of convincing evidence to support such value (Mayer, 2011; Pashler, McDaniel, Rohrer, & Bjork, 2008). According to Mayer (2011, p320), "researchers and practitioners must search long and hard for the educational implications of styles research". Towards this end, this trait was integrated in the modified model by assuming that catering an online course in accordance with a particular style of learners may enhance their perceived usefulness and satisfaction. In the authors' best knowledge, literature did not test the causal link among learning styles, perceived usefulness, and perceived satisfaction by accommodating a learning context as per the particular dichotomies of learning styles in the TAM.

***H1a**: Learners' learning styles positively affect perceived usefulness (PU) in online learning.*

***H1b**: Learners' learning styles positively affect perceived satisfaction (PS) in online learning.*

3.2 Surface level factor (Gender diversity)

Many studies have investigated the implications of gender diversity on learning experience, for instance, in terms of outcome and satisfaction (Al-Azawei & Lundqvist, 2014; Hong, 2002; Lau & Yuen, 2009). However, the results were inconsistent suggesting further research (Shore et al., 2009). Gefen & Straub (1997) stated that women's responses to certain situations tend to be different than men's. This suggests that IT theories and technology acceptance research should attempt to consider gender differences. Cagiltay, Yildirim, & Aksu (2006) demonstrated that males and females are inclined to adopt different learning methods; women preferred a liner approach, whereas men tend to adopt a non-linear one. Gefen & Straub (1997) extended TAM by adding gender as a one of the fundamental cultural differences. The inspection of the incorporated sample did not show that gender affected e-mail adoption. However, men and women differed in their perceptions. Moreover, Ong & Lai (2006) recommended that researchers should consider gender diversity during the investigations of e-learning theories. Significant dissimilarities were found between men and women with regard to PU, PEOU, computer self-efficacy, and behavioural intention to adopt e-learning (Ong & Lai, 2006). Based on such literature, gender diversity was included to examine the causal relationship among these factors.

***H2a**: Learners' gender diversity positively affects perceived usefulness (PU) in online learning.*

***H2b**: Learners' gender diversity positively affects perceived satisfaction (PS) in online learning.*

***H2c**: Learners' gender diversity positively affects perceived ease of use (PEOU) in online learning.*

3.3 Cognitive factor (online self-efficacy OSE)

Self-efficacy was defined as a learner's cognitive beliefs affecting their behaviour when using a technology (Wu, Tennyson, & Hsia, 2010). In this context, the technology refers to online learning. Some studies identified anxiety and computer skills as parameters influencing the online learning experience (Hong, 2002; Sun et al., 2008). However, we excluded them from our study, as all subjects, except for two, belonged to the computer science field. In addition to perceived usefulness and ease of use as two identified cognitive factors in the TAM, we included online self-efficacy (OSE) as another cognitive construct because e-learning had recently been used in Iraq.

As literature indicates, the effect of OSE on learning experience has been empirically investigated (Johnson et al. 2008; Liaw 2008; Ong & Lai, 2006; Sun et al. 2008). Based on the concept of OSE as a reflection of learners' expectations, it was anticipated to be a significant factor which might influence PU (Ong & Lai, 2006). Investigating the causal link between self-efficacy (SE) and PEOU showed the importance of this factor to predict the latter (Ong & Lai, 2006; Weiyin, James, Wai-Man, & Kar-Yan, 2001) . Additionally, Sun et al. (2008) found that SE was a predictor of PS. Accordingly, we suggest that OSE is an influential factor in online learning.

***H3a**: Online self-efficacy (OSE) positively affects perceived usefulness (PU) in online learning.*

***H3b**: Online self-efficacy (OSE) positively affects perceived ease of use (PEOU) in online learning.*

***H3c**: Online self-efficacy (OSE) positively affects perceived satisfaction (PS) in online learning.*

3.4 Perceived usefulness (PU)

Perceived usefulness was defined as "the degree to which an individual believes that using a particular system would enhance his or her performance" (Davis, 1986, p26). It was suggested that perceived usefulness (PU) has a significant impact on accepting a technology, and that it can explain a user's attitude (Davis, 1986). As shown in literature, PU was a substantial predictor of perceived satisfaction weather in blended or online learning (Liaw, 2008; Sun et al., 2008). The criteria of Learners when rating the usefulness of a technology rely on their expectation that a technology will aid towards outcome amelioration and goal achievement. Online learning represents a new trend in the developing countries, and more specifically Iraq. Thus, we hoped to investigate learner satisfaction of online learning in accordance with this factor.

***H4**: Perceived usefulness (PU) positively affects perceived satisfaction (PS) in online learning.*

3.5 Perceived ease of use (PEOU)

Perceived ease of use was defined as "the degree to which an individual believes that using a particular system would be free of physical and mental effort" (Davis, 1986, p26). Hence, TAM and the Technology Acceptance Model 2 (TAM2) illustrated PEOU significance in determining PU and users' attitudes towards a technology (Davis, 1986; Venkatesh & Davis, 2000). It directly associates with PS because learners, more specifically in non-mandatory courses, are reluctant to continue using an online system if they face difficulties in employing it and may be prone to dropping a course or to searching for an alternative learning environment. Therefore, literature has linked PEOU with PS (Liaw, 2008; Sun et al., 2008). Grounded on such findings, PEOU was regarded as an influential factor on PU and PS.

***H5a**: Perceived ease of use (PEOU) positively affects perceived usefulness (PU) in online learning.*

***H5b**: Perceived ease of use (PEOU) positively affects perceived satisfaction (PS) in online learning.*

3.6 Perceived satisfaction (PS)

Investigating factors that influence learner satisfaction can play a vital role in understanding the path to success in an e-learning situation and it is hoped that consideration of such variables will contribute to an enhancement of learning experience. Learner satisfaction means

> easily reflects outcomes of reciprocity that occur between students and an instructor instructor…keeps an instructor on his or her toes as a double-check to make sure that material is relevant and current or that students see themselves learning.… (Guolla, 1999 as cited in Thurmond, Wambach, Connors, & Frey, 2002, p176).

Furthermore, Wu, Tennyson, & Hsia (2010) define learner satisfaction as the acquisition of all the advantages a learner aims to receive from learning, as per his behavioural beliefs and attitudes. Based on these definitions, PS is a key factor stemming from the completion of a learning task, where the aimed outcomes derive enjoyably. Bolliger & Wasilik (2009) accounted perceived satisfaction as a vital aspect to continue learning.

Educational institutions should give special consideration to meet learner satisfaction. From a commercial perspective, students are similar to customers. Thus, their learning needs should be met. From a learning point of view, students cannot learn properly if they feel that there are environmental or personal barriers preventing them to achieve their objectives. As a result, Donohue & Wong (1997) indicated that learners level of motivation is affected by their satisfaction.

Many variables can influence perceived satisfaction. Bolliger & Martindale (2004) discussed three factors that represent a central key of learner satisfaction in online learning: instructors, technology, and interactivity. The learner factor, however, is not of less importance than these factors. Table 1 chronologically summarises some studies that examined the impacts of several variables on learner satisfaction.

Table 1: Literature review

Author(s)	sample	Examined variables
Hong (2002)	26	Computer experience, gender, age, scholastic aptitude, learning styles, student–instructor and student–student interactions, perception of the course activities, asynchronous, and time spent on the course.
Bouhnik & Marcus (2006)	-	Interaction (learner-content, learner-teacher, learner-learner and learner-system).
Johnson, Hornik, & Salas (2008)	345	Application-specific computer self-efficacy (AS-CSE), technology usefulness, interaction and social presence.
Sun et al. (2008)	295	Learner dimension (Learner attitude towards computers, Learner computer anxiety and Learner Internet self-efficacy), Instructor dimension (Instructor response timeliness and Instructor attitude towards e-Learning), Course dimension (E-Learning course flexibility and E-Learning course quality), Technology dimension (Technology quality and Internet quality), Design dimension (Perceived usefulness and Perceived ease of use) and Environmental dimension (Diversity in assessment and Learner perceived interaction with others).
Wu, Tennyson, & Hsia (2010)	212	Cognitive variables (self-efficacy and performance expectations), Technological environment (system functionality, content feature) and Social environment (interaction).
Cole, Shelley, & Swartz (2014)	553	Interaction (including communication), convenience, structure (including clarity and instructor's facility with online instruction), learning style, platform, gender, age and the level of study.

4 Research Methodology

4.1 Context

Moodle was installed on the University of Reading server under the name of *Arabic Programming*. It is available on http://arabic-programming.reading.ac.uk/ and offers different courses for Arabic learners who are interested in computer science and programming languages. Anyone can register with the system and have access to all provided courses.

Learners who registered in a web design course in the online learning system were requested to participate in the study. The course was delivered in seven weeks from the middle of October to December 2014 to teach web design using Hypertext Markup Language (HTML) and Cascading Style Sheet (CSS). Every lecture included videos, written text as a pdf file, figures, and examples. The video lectures were divided into small parts because of the low internet bandwidth in Iraq. Each lecture comprised at least two to five videos and lasted between 10 to 15 minutes. Furthermore, four lectures included self-assessment tests. Forums and wiki were activated to discuss course content, and questions were posted that had to be answered by participants. Although the written lectures were in English, the course was taught and explained in the Arabic language.

The course was intentionally designed to serve one pole in each dimension of FSLSM (Felder & Silverman, 1988), more specifically, it considered the characteristics of active, sensing, visual, and sequential learners.

- Processing (active/ reflective): An active learner prefers to do something, self-assessment and group work. These preferences were served by adopting learning-by-doing approach, adding self-assessments to four lectures, and activating interaction tools in the system to allow learners to work with their peers.
- Perception (sensing/ intuitive): A sensing learner tends to prefer facts and no complex concepts. This course was delivered for novice learners who do not have previous knowledge of web design. Therefore, it only entailed general information about web design without any complex concepts and without high level programming that required more thinking. Furthermore, several examples were provided with each lecture to meet the preferences of this style.
- Input (visual/ verbal): A visual learner tends to use pictorial materials rather than written text. Although written lectures were provided, they included only the head points. Therefore, the course relied on video lectures and figures to explain the content, and thus served the preferences of a visual learner rather than a verbal one. Overall, the course consisted of 27 short video lectures.

- Understanding (sequential/ global): A sequential learner prefers a step-by-step learning approach and focuses on surface details before getting the whole picture. The course was sequentially presented by providing all details regarding the principles of web design in HTML and CSS, starting from scratch to cover all relevant details, and then to develop learners' knowledge step by step. In the last lecture, all delivered materials were connected by designing a whole website which used all explained content. As such, sequential learners who are patient with details may find the course more suitable for their needs.

The purpose of this design was to quantitatively compare user satisfaction in accordance with their styles and preferences. Furthermore, in order to avoid any bias in the responses to the distributed questionnaires, learners were not informed that the course design served particular preferences. Figures 2 and 3 illustrate the main page of the course and the use of multimedia instructions in teaching and learning.

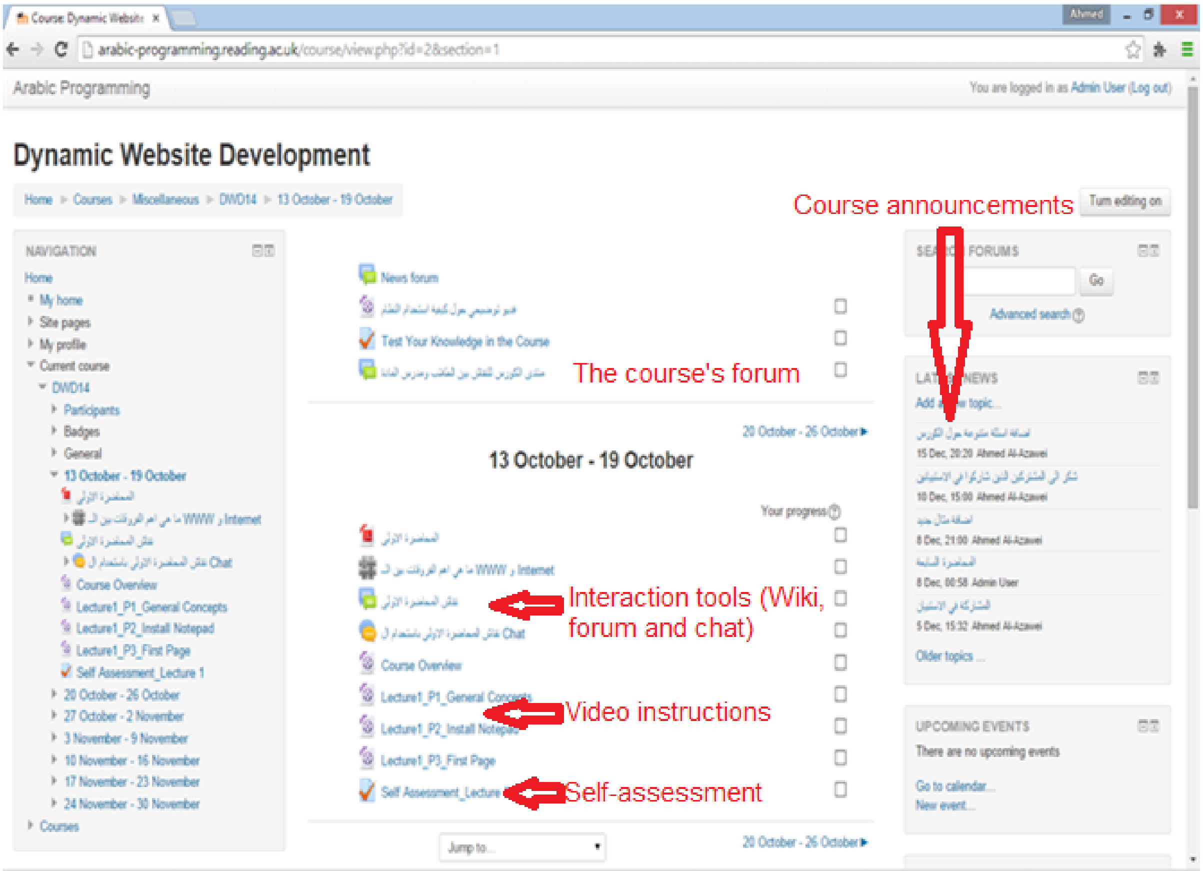

Figure 2: The course's main page.

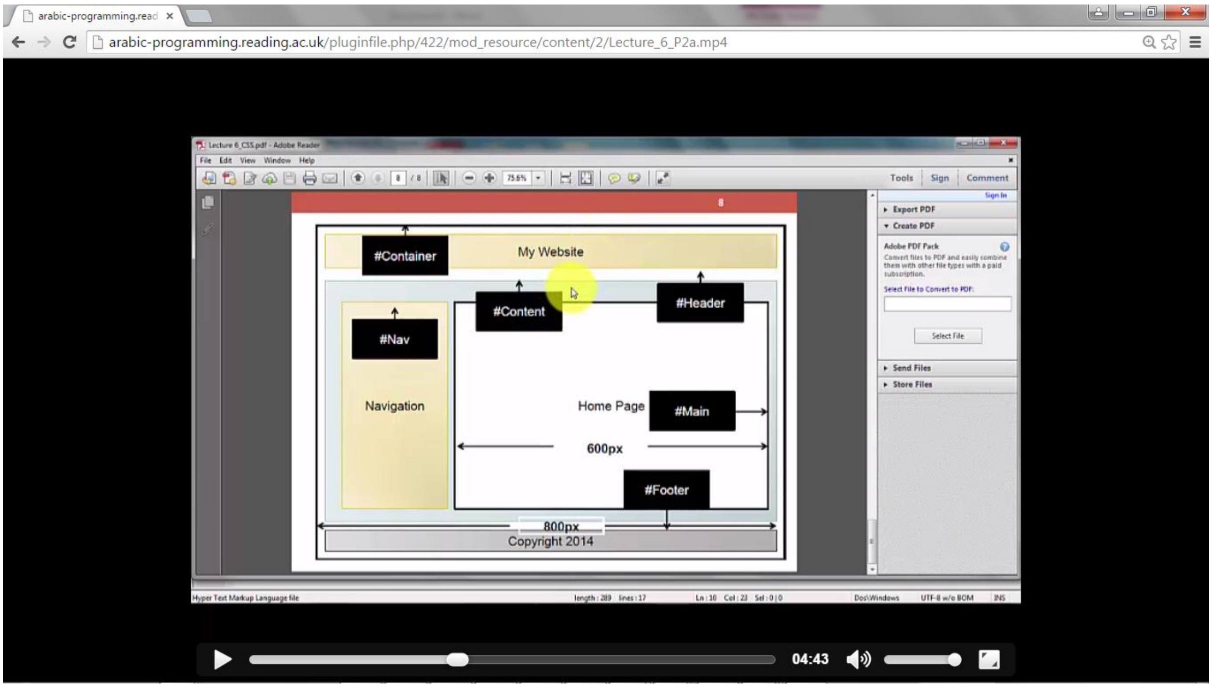

Figure 3: The multimedia instructions.

4.2 Participants

A short video was posted on Facebook to introduce the course and show users how to self-enrol. In addition, many lecturers in different computer science colleges in Iraq were contacted to encourage their students to participate. A total of 144 learners registered on the course. In total, 88 (61.11%) learners filled in the distributed questionnaires. However, 18 users who filled out either the learning styles questionnaire or the standard survey were excluded from this investigation. As such, 70 (48.61) learners represented the total subjects of this study. The demographic features of participants are presented in Table 2. The area of study of all participants was IT or computer science, except for two. However, these two cases were not excluded from the analysis because the overall findings would not be affected by such small rate (2.8%).

Table 2: Demographic features (N=70)

Item	N (%)	Item	N (%)
Gender:		**Area of Study:**	
Male	27 (38.6)	Computer Science or Information Technology	68 (97.1)
Female	43 (61.4)	To some Extent Relate to Computer Science	1 (1.4)
		Others	1 (1.4)
Level of Study:		**Age Group:**	
Undergraduate	59 (84.3)	18-21	57 (81.4)
BSc	7 (10)	22-25	7 (10)
MSc	1 (1.4)	26-29	1 (1.4)
Postgraduate	3 (4.3)	30-33	2 (2.9)
		34-37	1 (1.4)
		38-41	2 (2.9)

4.3 Data collection

In order to gather data, online-based surveys were used. This comprised two questionnaires to identify the demographic features of participants, learning styles, and the identified factors. The questionnaires included a brief explanation about the objective of carrying out this research, also guaranteeing confidential manipulation of all data.

During week six, subjects were requested to participate in the video lectures, using the announcement page of the Moodle system and sending an email to all learners. After ten days, the URLs of both instruments were

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announced again on the Moodle and a reminder email was sent to all participants. The questionnaires were administrated in December 2014 and for approximately a month. All questions in both instruments were translated into the Arabic language. Two PhD students at two different universities in the UK who speak Arabic as a mother language checked the translation in order to verify it. According to their feedback, some questions were modified.

4.3.1 The Index of Learning Styles (ILS)

This psychometric instrument was proposed in order to infer learning styles in accordance with FSLSM (Felder & Silverman, 1988). The questionnaire comprised 44 forced-choice questions. Eleven questions were asked to identify each of the four dimensions (active/ reflective, sensing/ intuitive, visual/ verbal, and sequential/ global) of FSLSM (Felder & Soloman, n.d.). For each question users could choose either ‘a’ or ‘b’. The two options corresponded to one or the other pole in each dimension for instance, ‘a’ for active style and ‘b’ for reflective one. This design allowed for the identification of mild, moderate, and strong preferences in each dimension. In order to carry out the statistical analysis with regard to learning style dimensions, the following procedure was followed. Initially, 1 was assigned to all ‘a’ options and 0 to all ‘b’ options. This produced integer values ranging from 0 to 11. Then, Felder & Spurlin (2005) suggested defining, for example, for the processing (active/ reflective) dimension, a score of 0-1 as a ‘strong-reflective’, 2-3 as a ‘moderate-reflective’, 4-5 as a ‘mild-reflective’, 6-7 as a ‘mild-active’, 8-9 as a ‘moderate-active’, and 10-11 as a ‘strong-active’. Figure 4 illustrates the scores distribution of learning styles. The main tendencies of students were towards active (68.5%), sensing (72.8%), visual (75.7%), and sequential (65.7%) styles (including those with mild preferences).

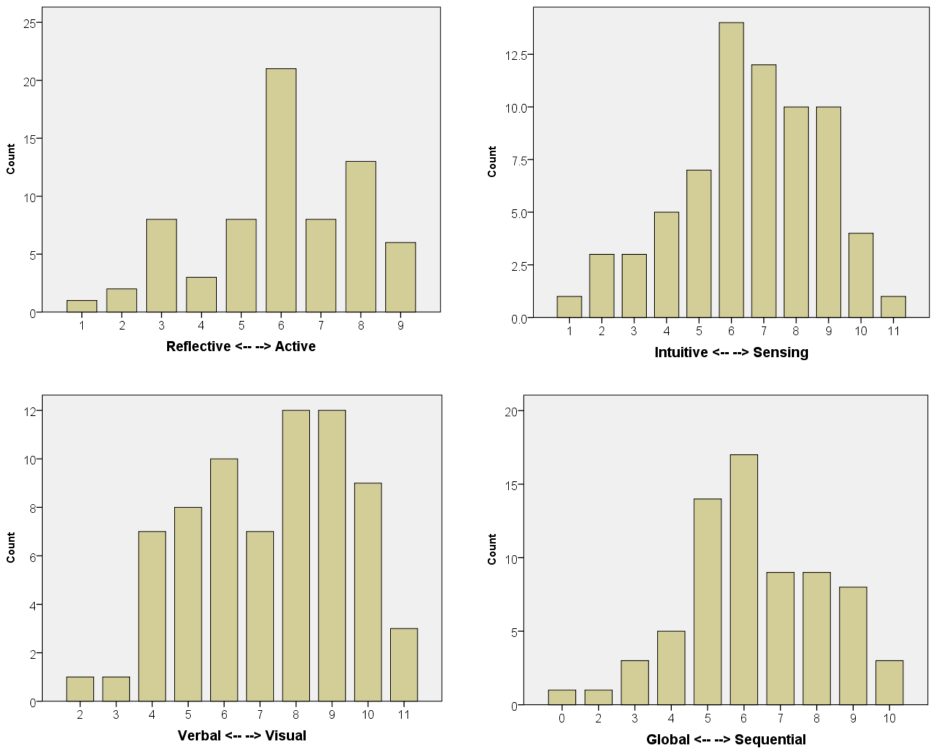

Figure 4: Distribution of learning style scores

4.3.2 A standard questionnaire

To begin with, three e-learning experts examined the questionnaire in order to improve its face-structure. As a result, some questions were excluded, while others were modified. The questionnaire included the following parts:

- *Demographic data*: gender, age group, level of study, area of study, internet, and e-learning experience. The last two features were identified by using a 7-point Likert scale ranging from 1 for ‘strongly disagree’ to 7 for ‘strongly agree’.

- *The closed-ended questions*: sixteen questions were used to identify the four factors: OSE (5 indicators), PU (3 indicators), PEOU (3 indicators), and PS (5 indicators). A 7-point Likert scale ranging from 1 for 'strongly disagree' to 7 for 'strongly agree' was used. This scale was adopted in order to give learners more flexibility to express their preferences. The questions were self-developed and adapted from literature (Johnson et al., 2008; Liaw, 2008; Sun et al., 2008; Piccoli et al., 2001; Wu et al., 2010). Appendix A presents the items of each construct in the proposed model.

- *An open-ended question*: this was an optional question that learners can answer or ignore. It aimed to qualitatively identify learners' perspectives with regard to the advantages and disadvantages of online learning and attending this course via internet. Although all comments of the nine participants who answered this question were positive, the qualitative analysis was excluded due to the small number of responses.

4.4 Analysis techniques

In order to investigate the proposed hypotheses, the software SPSS (Statistical Package for the Social Sciences) version 22 and SmartPLS version 3.0 for Windows 7 were used. Different descriptive and inferential statistics were conducted. This included the computing of mean (M), frequency, standard deviation (SD), Cronbach's α, Pearson's correlation, factor analysis, and PLS method. The p value at 0.05 was adopted to investigate the significant correlation between variables.

5 Results and discussion

The participants demonstrated good knowledge of the internet, and familiarisation with online learning. This was unsurprising because, except for two, all were studying or have graduated from computer science or information technology schools. However, they were not very experienced at using the internet (*M*=4.90, *SD*=1.571) and e-learning (*M*=4.70, *SD*=1.662). This result was compatible to our initial expectations because the use of such technologies, particularly online learning is still in its infancy in Iraq. Pearson's coefficient showed a mild, but significant correlation among internet, e-learning experience, and PS (*r*=0.28, *P*=0.018 and *r*=0.24, *P*=0.041) for both variables respectively.

5.1 Differences between groups

Pearson correlation coefficient of gender diversity among PU, PEOU, and PS was also computed before conducting the PLS model. This was essential prerequisite to understand the level of correlation between independent and dependent factors. The results did not demonstrate any significant correlation (r=-0.098, P=0.41), (r=-0.076, P=0.53), and (r=-0.074, P=0.54), for the three factors respectively. In order to reveal any significant differences among learning styles, PU, and PS, one-way ANOVA was conducted. The results are reported in Table 3. It is clear that there are no significant differences between learning style groups and the dependent factors (PU and PS).

Table 3: One way ANOVA findings examining variation in PS and PU for learning style groups

Perceived Satisfaction (PS)						Perceived Usefulness (PU)					
Learning style	**M**	**SD**	**F**	**df**	**P**	**Learning style**	**M**	**SD**	**F**	**df**	**P**
Active	5.75	0.99	1.522	1,68	0.22	**Active**	5.97	1.0	2.744	1,68	0.102
Reflective	6.03	0.58				**Reflective**	6.36	0.68			
Sensing	5.91	0.83	1.32	1,68	0.25	**Sensing**	6.08	0.99	0.023	1,68	0.88
Intuitive	5.64	1.03				**Intuitive**	6.12	0.73			
Visual	5.84	0.82	0.002	1,68	0.96	**Visual**	6.05	0.96	0.506	1,68	0.47
Verbal	5.83	1.10				**Verbal**	6.23	0.81			
Sequential	5.79	0.99	0.373	1,68	0.54	**Sequential**	6.13	0.99	0.190	1,68	0.66
Global	5.93	0.66				**Global**	6.09	0.92			

5.2 Instrument properties

Pallant (2013) indicated that Cronbach's coefficient alpha is a widely used indicator to measure the construct-internal consistency of a measurement. The overall result indicated high-consistency reliability (α=0.90). The αs, as presented in Table 6, showed that all factors were at a good level of reliability. For further investigation, Pearson coefficient correlation was used to conduct the inter-scale and total items correlation. There is a significant correlation between all scales and most items as presented in Tables 4 and 5. However, the highest correlation among scales is 0.585 between perceived usefulness and perceived satisfaction. The multicollinearity assumption was not violated as the results of tolerance and VIF (Variance Inflation Factor) revealed (Table 4).

Table 4: Pearson correlation coefficient (Inter-scales correlation)

	PU	PEOU	PS	Tolerance	VIF
OSE	0.488**	0.558**	0.410**	0.634	1.578
PU		0.515**	0.585**	0.677	1.478
PEOU			0.418**	0.612	1.635

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

According to Pallant (2013), in order to carry out the factor analysis test, the correlation matrix should reveal a correlation of at least 0.3 among some items. Furthermore, Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) as commonly used measures to check whether the factorability of data achieves less or equal to 0.05 and 0.6 as a minimum value for both tests respectively. These criteria were matched in this analysis. The KMO was 0.815 and the Bartlett's test of sphericity was significant at p less than 0.001. As such, the results support the factorability of the correlation matrix.

The Principle Components Analysis (PCA) extracted the presence of 4 factors to explain 69.5% of variance. Factors 1, 2, 3, and 4 loaded all items of the four scales as illustrated in Appendix B. The "scree plot" of eigenvalues (Figure 5) also showed a smooth decrease in eigenvalues after factor 4. The four-factor model perfectly identified the four constructs and strongly loaded all items. For further analysis, Wixom & Todd (2005) stated that the convergent and discriminant validity can be proven if the items' load on their associated constructs is above 0.5 and higher than their loaded across factors (Appendix B). Hair, Black, Babin, Anderson, & Tatham (2006) stated that the convergent validity can be established when the values of average variance extracted (AVE) and composite reliability (CR) are higher than the acceptable level of 0.5 and 0.7. Furthermore, if the variance shared between any variable and other factors in the tested model is less than the variance that a variable shares with its own factors, discriminant validity can be supported (Fornell & Larcker, 1981). Table 6 illustrates that AVE and CR exceeded the thresholds to support the convergent validity and the discriminant validity was advocated as well.

Table 5: Pearson correlation coefficient (Inter-items correlation)

	OSE					PU			PEOU			PS			
	1	2	3	4	5	1	2	3	1	2	3	1	2	3	4
OSE2	.612**	1													
OSE3	.269*	.362**	1												
OSE4	.478**	.619**	.513**	1											
OSE5	.521**	.517**	.526**	.530**	1										
PEOU1	.301*	.402**	.316**	.525**	.326**	1									
PEOU2	.357**	.359**	.268*	.418**	.217	.541**	1								
PEOU3	.397**	.333**	.390**	.440**	.323**	.444**	.496**	1							
PU1	.440**	.355**	.268*	.318**	.404**	.234	.509**	.464**	1						
PU2	.262*	.341**	.201	.320**	.207	.229	.400**	.349**	.599**	1					
PU3	.318**	.374**	.281*	.409**	.425**	.301*	.400**	.334**	.601**	.669**	1				
PS1	.175	.310**	.298*	.337**	.265*	.201	.254*	.423**	.503**	.509**	.409**	1			
PS2	.246*	.283*	.251*	.374**	.289*	.214	.245*	.451**	.487**	.484**	.537**	.698**	1		
PS3	.232	.226	.184	.468**	.410**	.323**	.340**	.316**	.509**	.420**	.448**	.698**	.556**	1	
PS4	-.029	.199	.115	.177	.159	.071	.159	.240*	.305*	.302*	.203	.652**	.508**	.515**	1
PS5	.116	.365**	.230	.451**	.413**	.355**	.252*	.414**	.397**	.337**	.421**	.650**	.536**	.733**	.663**

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

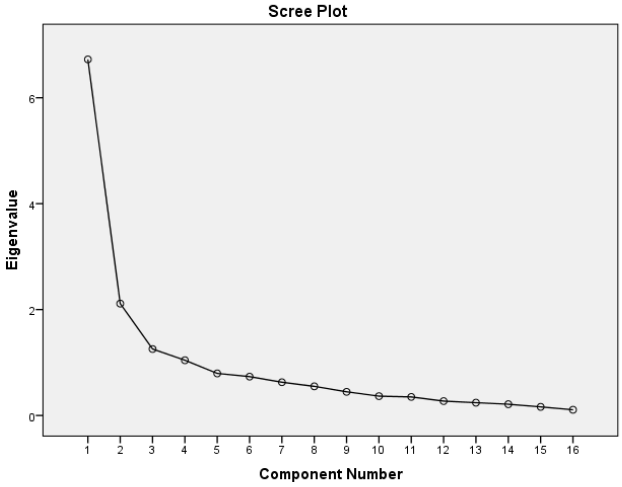

Figure 5: Scree plot for factor analysis of the questionnaire (n=70)

Table 6: Findings of the measurement model

Latent factor	AVE (>0.5)	CR (>0.7)	Cronbach's α	Discriminant validity			
				OSE	PEOU	PS	PU
OSE	0.598	0.881	0.830	0.773			
PEOU	0.661	0.854	0.745	0.575	0.813		
PS	0.696	0.920	0.891	0.433	0.440	0.834	
PU	0.748	0.899	0.832	0.496	0.518	0.600	0.865

5.3 Hypotheses investigation

PLS-SEM was used to test the path associated in the proposed model. This is due to many reasons: it is applied to reveal the relationship between independent and dependent variables, specifically, when a dependent factor is used as an independent one in a model (PEOU and PU in this study) (Tarhini et al., 2015), it is adequate for small sample size (Barrio-garcía, Arquero, & Romero-frías, 2015; Chin, 1998; Yi & Hwang, 2003), and it was predominant in prior TAM related work (Barrio-García et al., 2015; Yi & Hwang, 2003).

The study aimed to modify the TAM by integrating several learner factors to evaluate learner satisfaction in online learning instead of attitude to use a technology. Generally, four hypotheses were retained and seven were rejected. Table 7 depicts that neither learning styles nor gender diversity showed any direct significant effect on PU, PEOU, and PS, OSE had direct significant influences on PU and PEOU, PEOU had direct significant effect on PU, and PU was the best predictor of PS. In Figure 6, the path associated between variables after carrying out the PLS modelling is presented. The four dimensions of learning styles were abbreviated to $\boldsymbol{\beta}_{Proc}$, $\boldsymbol{\beta}_{Per}$, $\boldsymbol{\beta}_{Inp}$, and $\boldsymbol{\beta}_{Und}$ for Processing, Perception, Input, and Understanding respectively. The independent factors explained 44.8% of variance where PU was the strongest predictor.

Table 7: Hypotheses analysis

Hypotheses	R^2	*Standardised estimate*						
		Direct effect	*t*	*P*	*Indirect effect*	*t*	*Total effect*	**Finding**
Dependent PU	**0.340**							
H5a: PEOU→ PU		0.366	2.277	0.019			0.366	Supported
H3a: OSE → PU		0.268	2.010	0.037	0.213	2.016	0.481	Supported
H2a: Gender → PU		0.001	0.008	0.99	0.011	0.308	0.0122	Rejected
H1a: LS → PU								
Processing		-0.069	0.596	0.53			-0.069	Rejected
Perception		-0.079	0.568	0.58			-0.079	
Input		0.069	0.673	0.51			0.069	
Understanding		-0.009	0.067	0.95			-0.009	
Dependent PEOU	**0.331**							
H3b: OSE → PEOU		0.581	4.185	<0.001			0.581	Supported
H2c: Gender → PEOU		0.030	0.313	0.74			0.030	Rejected
Dependent PS	**0.448**							
H5b: PEOU → PS		0.069	0.435	0.65	0.171	1.836	0.240	Rejected
H4: PU → PS		0.467	3.210	0.002			0.467	Supported
H3c: OSE → PS		0.245	1.214	0.22	0.265	2.107	0.510	Rejected
H1b: LS → PS								
Processing		-0.076	0.637	0.48	-0.032	0.609	-0.108	Rejected
Perception		0.259	1.759	0.067	-0.037	0.548	0.222	
Input		0.087	0.910	0.35	0.032	0.680	0.119	
Understanding		-0.227	1.826	0.076	-0.004	0.070	-0.231	
H2b: Gender→ PS		-0.033	0.288	0.76	0.007	0.155	-0.025	Rejected

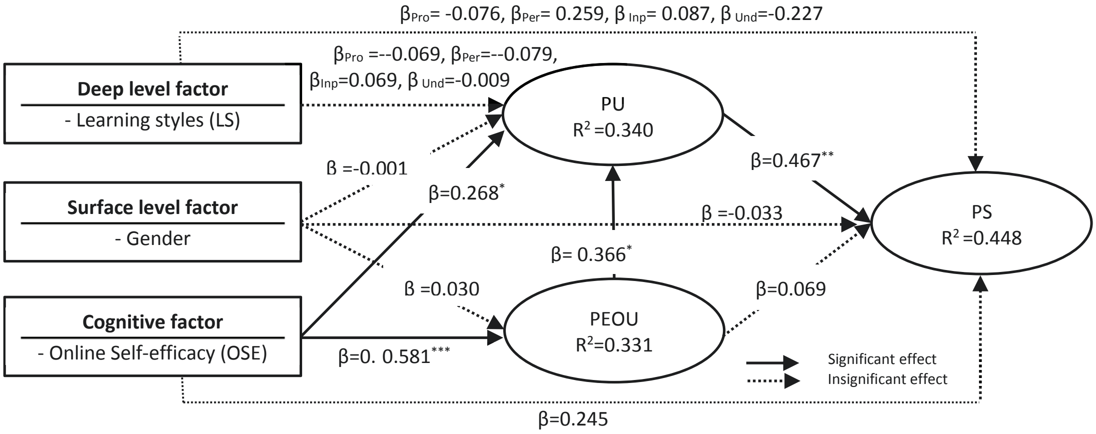

Figure 6: The results of the proposed hypotheses

As presented in this analysis, learning styles did not seem to predict PU (H1a) and PS (H1b). Although literature did not investigate the effects of learning styles on PU in an adaptable learning setting, we suggested such influence based on learning styles hypothesis. Contrary to our assumption, H1a was rejected because learning style dimensions were not predictors of PU as shown in Table 7. With regard to H1b, our result is in agreement with the findings of Hong (2002) that learning styles did not significantly influence PS. Cheng & Chau (2014) argued that learning styles are significantly associated with online participation and the latter, in turn, is associated with learner satisfaction. This result indirectly relates learning styles with PS. However, we deliberately designed the online learning environment to match the preferences of particular poles in the FSLSM. This adaptation presented an insignificant effect among the four dimensions and PS (Table 7), whereas Cheng & Chau (2014) did not explore this point. Accordingly, this research indicates that other factors are more likely to affect learner satisfaction than learning styles. It could be argued that the online environment matched the preferences of the majority of participants because most of them were tend to active, sensing, visual, and sequential. Nevertheless, the mean differences of PS for the dichotomies were not substantial enough to confirm our conclusion. This discussion was also supported by the findings of ANOVA test (Table 4). This means that regardless of matching or mismatching groups, learning styles as a factor cannot predict PU and PS. In addition to the theoretical critique regarding learning styles (Mayer, 2011; Pashler et al., 2008), this analysis adds more empirical debate with aspect to the implications of this trait.

Pertaining to gender diversity hypotheses, Ong & Lai (2006) integrated gender diversity in TAM to investigate e-learning acceptance. The study indicated the significance of gender differences. Male perceptions of computer self-efficacy, PU, and PEOU were significantly higher than female ones, and then the intention to use e-learning was different. In contrast, Gefen & Straub (1997) indicated that PU and PEOU for women was significantly higher than men. Such results were inconsistent with our findings, as gender was neither a predictive of PU ($\beta_{Gender\rightarrow PU}$= -0.001, P=0.994) nor PEOU ($\beta_{Gender\rightarrow PEOU}$= -0.030, P=0.754). Based on this analysis, H2a and H2c were rejected. Furthermore, H2b suggested that PS was significantly affected by gender diversity. Contrary, PLS did not show such significant relationship ($\beta_{Gender\rightarrow PS}$=-0.033, P=0.774). This result is in accordance with studies that pointed out gender was not an affective factor to predict learner satisfaction (Hong, 2002; Vanderheyden & De Baets, 2015). To conclude, literature has produced inconsistent results concerning the value of gender diversity. This might be explained by cultural differences because gender was accounted as one of the aspects of cross-cultural differences (Gefen & Straub, 1997).

Following online self-efficacy (OSE) hypotheses, this factor was a predictive of PU (H3a) and it was a strong predictor of PEOU (H3b) where the results were ($\beta_{OSE\rightarrow PU}$= 0.268, P=0.045) and ($\beta_{OSE\rightarrow PEOU}$= 0.581, P<0.001) for both hypotheses respectively. These results are consistent with other studies, for instance, Ong & Lai (2006). We also assumed a causal link between OSE and PS, as learners may be unsatisfied if they were not confident enough to use this technology and it represented new experience for them (H3c). However, this hypothesis was not confirmed ($\beta_{OSE\rightarrow PS}$= 0.245, P=0.225) to support the finding of Liaw (2008), whereas Sun et al. (2008) found that it was a predictor of PS. However, as mentioned previously, the sample included current students or graduates of computer science. Therefore, to some extent their OSE was over the expected level, as such other factors were more likely to predict learner satisfaction.

With regard to PU hypothesis (H4), this research supported the findings of Barrio-garcía, Arquero, & Romero-frías (2015), Davis (1986), Drennan et al. (2005), Venkatesh & Davis (2000), and Sun et al. (2008) to indicate that PU was the strongest predictor of technology acceptance or learner satisfaction ($\beta_{PU\rightarrow PS}$= 0.467, P<0.001). This means that participants found online learning to be a useful technology to achieve their goals and improve learning outcomes and this, in turn, undoubtedly affects their satisfaction. Specifically, it represents new experience for Iraqi students. Thus, in order to ensure continuous use of a learning technology, useful and interactive teaching methods that can promote academic achievement should be used.

Following PEOU hypotheses, as assumed in the TAM and TAM2, PEOU was a direct determinant of PU (Davis, 1986; Venkatesh & Davis, 2000). Our analysis of H5a verified this assumption ($\beta_{PEOU\rightarrow PU}$= 0.366, P=0.023). Such result supported the previous literature (Davis, 1986; Ong & Lai, 2006; Venkatesh & Davis, 2000). Tarhini et al. (2015), on the other hand, found that these factors are uncorrelated. Furthermore, contrary to our assumption that PEOU will significantly affect PS (H5b), the analysis rejected this hypothesis ($\beta_{PEOU\rightarrow PS}$= 0.069, P=0.664). Similarly, Drennan et al. (2005) and Tarhini et al. (2015) revealed that PU was a determinant of PS or attitude to use a technology, whereas PEOU was not. On the other hand, Sun et al. (2008) pointed out the significance of PEOU to determine learner satisfaction . Our finding can be interpreted according to the experience level of participants in online learning because all, but two, came from Information Technology and Computer Science majors. Therefore, they did not face any difficulty to work in that environment due to their individual skills. This justification can also be advocated by the interpretation of Tarhini et al. (2015) that PEOU is a critical factor in the early stage of adoption. Additionally, the significance of PEOU on e-learning or e-mail technologies was shown in the prematurity era of such technologies (Gefen & Straub, 1997; Ong & Lai, 2006; Venkatesh & Davis, 2000). Therefore, the maturity of current e-learning technologies may help learners to use them even if they are less experienced. In other words, this does not mean that PEOU is not a significant factor, however, it may mean that the use of superior and usable learning technologies supports delivering e-learning more easily.

In summary, the modified model explained 44.8% of variance. PU was the best predictor, whereas all other integrated factors did not show a direct significant contribution. In general terms, the overall results slightly enhanced the findings of the original TAM where the model typically explained 40% of variance (Venkatesh & Davis, 2000).

6 Implications and limitations

The overall results are promising because they are indicative of the high degree of satisfaction and perceived usefulness of Iraqi learners with regard to online learning. This should encourage the MHESR-I to establish an integrated infrastructure to extend the use of online learning or blended learning in public universities in order to improve learning quality and motivate students towards new learning technologies. Specifically, the contributions of the research are fourfold. To begin with, although it modified TAM to predict satisfaction instead of technology adoption, it moderately supported the original factors of the TAM in an Arabic population sample. On the other hand, all extended factors were not direct predictors of learner satisfaction. Moreover, the study contributed to the existing debate by pointing out the modest effect of learning styles on educational practice as indicated in other works (Mayer, 2011; Pashler et al., 2008). Some reported studies such as Brown (2007) qualitatively analysed the implications of learning styles on perceived satisfaction in an adaptive learning environment to indicate that this adaptation improved learner satisfaction albeit this trait did not influence academic performance. However, in order to investigate the effectiveness of learning styles on such factors, it is essential that learners are unaware that an online course is designed according to their individual preferences so that a placebo effect scenario is prevented. Our result may suggest that there is no need to personalise educational hypermedia systems (EHSs) according to this trait because students can easily adapt to different learning circumstances even if such environments do not address their individual preferences. Furthermore, the surface level factor (gender) is influenced by several cultural and environmental variables (Gefen & Straub, 1997). Therefore, we recommend further investigation to reveal the effectiveness of gender diversity in developing countries not least in regions were cultural customs impose restrictions on female education. Mixing quantitative and qualitative analysis can provide more in-depth understanding about the role of gender in such cultures. Finally, the cognitive factor (OSE) is directly linked with PU and PEOU, but its effect on PU and PS may also depend on other variables such as individual skills, user experience, and the maturity of a particular technology.

It is worth mentioning that this study is subject to many limitations. First, the sample size is quite small and homogeneous. Investigating larger and heterogeneous population can provide more reliable results. Thus, the findings of the study should be interpreted cautiously. Second, the data were collected from subjects who attended one online course. Hence, this may represent their subjective opinion regarding that individual course. Collecting data from different courses could allow for more encompassing interpretations.

7 Conclusion

Meeting user satisfaction represents a key factor for success in online learning. This study modified TAM to achieve this goal. The results showed that not all identified factors can predict perceived satisfaction. However, the perceived usefulness as an original factor in TAM represents the best predictor. Although online self-efficacy and perceived ease of use did not directly affect perceived satisfaction, this was explained according to the individual experience of learners and the maturity of a particular technology.

The study focused on the role of learning styles to determine learner satisfaction. Some of the learning tendencies were intentionally mismatched to serve only other styles. However, the results did not show any statistical significance among perceived satisfaction and the matched or mismatched groups. This means that variables other than learning styles may significantly affect learner satisfaction. Based on this result, it should be recommended that when researchers aim to investigate the pedagogical implications of learning styles, students should not be aware that an online course is designed in accordance with their styles, so that the placebo effect is prevented. In other words, if learners are informed that the course is adapted as per their individual preferences and styles, this might psychologically predispose them to positively respond to qualitative or quantitative questions. This may explain the contradictory findings regarding the implications of learning styles on learner satisfaction. In future work, a larger sample will be used to substantiate the findings. Additionally, it would be more feasible to collect data from a heterogeneous sample in order to avoid any bias that could be emerged in a homogeneous one. Other independent factors can be incorporated in order to enhance the model.

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Appendix A: The questionnaire items, mean, and standard deviation

Factors	M	SD
Online Self-efficacy (OSE):	5.08	1.12
1) I believe that I have the ability to post comments and respond to comments posted in the course discussion forum.	5.06	1.30
2) I believe that I have the ability to locate information on the course website.	5.43	1.29
3) I believe that I have the ability to use all Moodle features.	4.69	1.78
4) I feel confident using online learning systems after participating in this course.	5.44	1.28
5) I feel confident using online learning systems before participating in this course.	4.79	1.65
Perceived Ease of Use (PEOU):	5.44	1.00
6) I found that all functions can be used easily even with less experience in online learning.	5.53	1.17
7) I found that the online learning system can be used easily.	5.43	1.34
8) I found it is ease to do what I want in the online learning system.	5.39	1.15
Perceived Usefulness (PU):	6.09	0.92
9) I believe online learning is a useful learning tool.	6.09	1.15
10) I believe online learning is useful.	6.16	1.03
11) I believe online learning improves learning outcomes.	6.04	1.04
Perceived Satisfaction (PS):	5.84	0.89
12) I am satisfied with using online learning as a learning assisted tool.	5.77	1.01
13) I am satisfied with using online learning functions.	5.63	1.19
14) I am satisfied with my decision to take this course via Internet.	5.80	1.04
15) If I have an opportunity to take another course via Internet, I would gladly do so.	6.14	0.99
16) I feel that online learning served my needs well.	5.87	1.102

Appendix B: Principle component analysis and factor loading

			Factors			
		Factor loading (>0.7)	**1**	**2**	**3**	**4**
OSE	**OSE1**	0.739		***0.687***	0.389	
	OSE2	0.815		***0.725***		
	OSE3	0.670		***0.638***		
	OSE4	0.838		***0.685***		0.409
	OSE5	0.793		***0.824***		
PEOU	**PEOU1**	0.788		0.309		***0.805***
	PEOU2	0.833			0.395	***0.777***
	PEOU3	0.819				***0.591***
PU	**PU1**	0.863			***0.752***	
	PU2	0.861			***0.797***	
	PU3	0.870			***0.735***	
PS	**PS1**	0.892	***0.801***		0.341	
	PS2	0.806	***0.639***		0.455	
	PS3	0.851	***0.738***			
	PS4	0.766	***0.847***			
	PS5	0.852	***0.832***			
	Variance %		21.6	18.8	16.2	12.8

Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 6 iterations.
Loading less than 0.3 was omitted.