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GREEK WOMEN AS ARTIFICIAL INTELLIGENCE ENABLED ELEARNING USERS: THEIR PERCEPTION OF PLP, PLN, PLE INTO TAM AND IMPACT ON LEARNER'S ATTITUDE AND SATISFACTION

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ABSTRACT

The purpose of this research was to explore the perception of Greek women concerning the role of artificial intelligence (AI). AI can be used to improve them and make eLearning more adherent to the users. Also it can play an essential role in generating the right environment by matching the profile of the learner. The data was collected among 120 Greek women, who were working professionals and students who have ever used the eLearning module and wholly based on their perceptions, leading to self-perception bias. The current research is trying to integrate the user perception of personal learning network (PLN), personal learning profile (PLP), and personal learning environment (PLE) into the framework of the technology acceptance model and their impact on perceived ease of use (PEOU), perceived effectiveness (PE), and perceived usefulness (PU), to the overall attitude and satisfaction of the learners and finally to their intention to use eLearning platform. All three aspects of TAM i.e., PEOU, PE, and PU came significant but PLN did not come significantly. PLP impacted PEOU, PE, and PU but mainly significantly impacting perceived effectiveness. PU mediated the relation between PLE and attitude and satisfaction. It was seen that the PLE is affecting both perceived ease of use and perceived usefulness. Further satisfaction mediates between perceived ease of use and intention. The multi-group analysis also showed that the attitude and satisfaction level affecting intention to use the eLearning module differs across the two groups of women (working professionals and students).

Key words: personal learning profile, personal learning environment, personal learning network, eLearning, Greek women

INTRODUCTION

"The illiterates of the 21st century will not be those who cannot read and write, but those who cannot learn, unlearn, and relearn" ― Alvin Toffler. Twenty-two years since the beginning of the 21st century and Alvin Toffer's apothegm is becoming a reality as we all see the high demands in working areas for up skilling, reskilling and retraining.

Since the beginning of 2020 when the coronavirus pandemic started spreading all over the world many changes never seen before happened in our lives, even the closure of international borders and the lockdown of domestic economies. All levels of provided education faced the challenge to adapt to new needs and transform to new shapes but still to be efficient for teachers to teach and also to cultivate students. From the lowest levels of schooling through higher education institutions, the influence of modern technology has been felt. Thornton et al. (2004) suggested eLearning as a tool which could improve teaching and learning skills; its effectiveness lied in whether the tool was used properly. Khan (2005) defined eLearning as "an innovative approach for delivering well-designed, learner-centered, interactive, and facilitated learning environment to anyone, anyplace, anytime". Today, eLearning gave the opportunity to the academic community to provide teaching online in a more massive way all around the globe overcoming the time and space of the traditional educational system. Increasingly, college students relied on computers for learning and many higher education institutions, use ICTs to develop course materials, deliver and share course content. Also, ICTs promote lectures, presentations and facilitates communication (Ja'ashan, 2020).

According to Parker (2020) in recent years, there has been talk in the sector about blended and flexible learning, but the reality has been that online resources have supplemented the dominant mode of delivery, which was synchronous and in-person. Spurred by the pandemic, but probably coming anyway, is the reverse situation. Courses are designed to be delivered through technology — 'digital first' — and supplemented by face-to-face, human support. The ability to transform, as described by Alvin Toffer, will be the critical one for all education institutions to cultivate, so they can shape and respond to a changing world of education (Parker, 2020) The tipping point of a new world of education's era is here. As we read in Cope and Kalantzi's (2019) paper on "Education 2.0: Artificial Intelligence and the End of the Test" according to Schwab Klaus (2017) on one count, after the industrial revolutions of steam, electricity, and digitization, the next is Industry 4.0, a revolution in which artificial intelligence will be central. A majority of college students today have grown up using in their everyday life Internet, email, and instant messaging. Emerging technologies have impacted the way students research, develop and publish their work. The option to use familiar online technologies in online classrooms can benefit students by reducing their anxiety about unfamiliar material (Griffin & Minter, 2013). AI can be used as means of improving eLearning according to the profile of the user, which can overcome the absence of a facilitator who understands the individual need of a learner (Kashive et al, 2020)

ICT plays important role in enhancing the learning process of students but its effectiveness depends upon the level of acceptance and degree of usage within the student population (Teo, 2014). Al-Harbi (2011), in Ja'ashan's (2020) article, explained that different factors influence eLearning acceptance. Students' attitude toward eLearning is the most important factor in determining their intention to use eLearning. Students' decision to use eLearning is also determined by their subjective norm, i.e., the influence of people around them. Moreover, the perception of eLearning's accessibility plays a role in shaping the students' behavioral intention regarding eLearning acceptance. The study has adopted Montebello (2017) framework of personal learning network (PLN), personal learning profile (PLP), and personal learning environment (PLE), as it was used in the paper of Kashive et al. (2020), and tried to integrate the user perception of the three above factors, into the framework of the technology acceptance model, to see how they impacted on perceived ease of use (PEOU), perceived effectiveness (PE), and perceived usefulness (PU), how are they, directly or indirectly, important for shaping the right attitude and grant with satisfaction the women and finally how the Greek women's intention to use an eLearning module platform can be prognosticated.

In Europe there is a disparity between the internet usages of people according to their gender. This disparity although present in most countries, differs widely in its severity. In Europe only 17% of the almost 8 million employees in ICT are women. Reasons that discourage women to follow a digital career include their low digital skills and the female-unfriendly working conditions. The European Council (2018) called on the EU Member States and the Commission to prevent and combat gender stereotypes, to reduce gender segregation in the labour market, to promote the participation of women in ICT jobs, and to promote the development of basic digital skills for both women and men (Perifanou and Economides, 2020).

According to information from Statista Research Department by 2020, 16 percent of male internet users in Greece used the internet to take part in any form of online learning activities. Among women this share was slightly lower with 15 percent. Over the last five years, seven percent more men and seven percent more women indicated that they used the internet for this purpose (Statista Research Department, 2022).

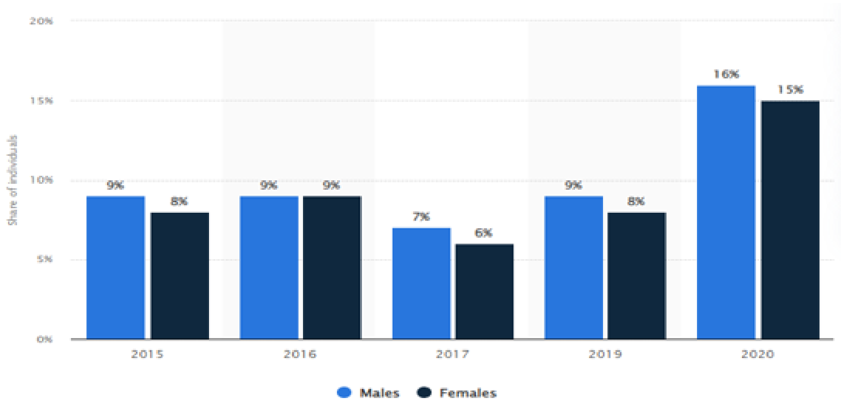

Figure 1- Share of people taking part in any form of online learning activities in Greece from 2015 to 2020, by gender © Statista

Due to previous researches of the writer on women in Greece and ICT use and in general the low percentages Greece demonstrates in the use of online learning activities by women this article have as research question the following:

Q-What factors (PLN, PLP,PLE, PEOU, PU, PE, ATT, S) act directly or indirectly to a woman's BI in Greece to use the eLearning platform?

LITERATURE REVIEW AND HYPOTHESES

Technology Acceptance Model (TAM): Among the many adoption models, TAM has been claimed to be the most influential and the most employed to predict the acceptance and use of various technologies due to its strength in theoretical basis and empirical support (Saga and Zmud, 1994). This model has been adopted and expanded in many studies in various types of technologies including e-mail, word processor, World Wide Web, enterprise resources planning (ERP) systems and proved high validity (Cakır and Solak, 2015). TAM was developed by Davis (1989) to explain the user's acceptance of information systems and the computer-usage behavior. The goal of TAM is to provide an explanation of the determinants of computer acceptance that in general being capable of explaining user behavior across a broad range of end-user computing technologies and user populations while at the same time being both parsimonious and theoretically justified (Davis et al, 1989). TAM specifies causal linkages between two key sets of constructs: (1) perceived usefulness (PU) and perceived ease of use (PEOU), and (2) user's attitude (AT), behavioral intentions (BI), and actual computer usage behavior (ACU) (Malhotra and Galetta, 1999). As demonstrated in the Theory of Reasoned Action, the Technology Acceptance Model postulates that the use of an information system is determined by the behavioral intention; but on the other hand, it asserts that the behavioral intention is determined by the person's attitude towards the use of the system and also by his perception of its utility.

Perceived Usefulness refers to a person's belief that the use of the computer will result in the achievement of personally relevant goals. It is defined as being the degree up to which a person believes that the use of a system will improve his performance (Davis, 1989). Perceived Ease of Use refers to a person's belief that using computers will be free of cognitive effort (Umrani and Ghadially, 2003). Davis (1986) advances that perceived ease of use also influences in a significant way the attitude of an individual through two main mechanisms: self-efficacy and instrumentality. Perceived Effectiveness (PE) of e¬Learning is determined to be the user's belief that e¬Learning is generally a valid and useful instructional tool and is a valuable component in a staff development program. Users who have not previously completed an e¬Learning module may be apprehensive of its value and its effectiveness as a training tool (Fuller, Vician, & Brown, 2006; Liaw & Huang, 2013 in Huprich, 2016).

Attitude and satisfaction for eLearning toward the behavior is defined as the individual's positive or negative feelings about performing the behavior, as a consequence, the degree to which performance of the behavior is positively or negatively valued. It is determined through an assessment of a person's beliefs regarding the consequences arising from behavior and an evaluation of the desirability of these attributes. Satisfaction according to Szymanski and Hise (2000) is considered as the users' judgment of their online overall experience over a period of time. The pleasure decided by the users and technological environment governs a system's implementation (Teo, 2014). Consequently, it can be said that the higher the satisfaction level of the user there are more chances for them to use the system (Liaw & Huang, 2013).

H1a. A learner's perceived ease of use toward eLearning impacts his/her attitude to learning.

H1b. A learner's perceived ease of use toward eLearning impacts his/her satisfaction with learning.

H2a. A learner's perceived usefulness toward eLearning impacts his/her attitude to learn.

H2b. A learner's perceived usefulness toward eLearning impacts his/her satisfaction with learning.

H3a. A learner's perceived effectiveness toward eLearning impacts his/her attitude toward learning.

H3b. A learner's perceived effectiveness toward eLearning impacts his/her satisfaction with learning.

Behavioral intention for using eLearning has long been recognized as an important mediator in the relationship between behavior and other factors, such as attitude, satisfaction, subjective norm, and perceived behavioral control (Ajzen, 1991; Ajzen and Fishbein, 1980). Behavioral Intention to use, according to

TPB, can be employed to directly predict behavioral achievement or actual behavior. When the person has complete control over the behavior in question, that is, when the behavior is completely voluntary, intentions alone should adequately predict behavior (Ajzen and Fishbein, 1980). In these cases, it is the existing behavioral intention to perform the behavior that can significantly predict actual future behavior.

H4a. A learner's attitude toward eLearning impacts his/her intention to use it.

H4b. A learner's satisfaction toward eLearning impacts his/her intention to use it.

Artificial intelligence (AI) and eLearning Artificial intelligence (AI) has become a mainstay in virtually all aspects of human life. And now, its presence is reinforcing education in the aspect of eLearning more than any other modern technology. Today, AI impacts the modern educational system in the areas of adaptive learning, virtual teachers and lecturers, customized digital learning interfaces, automated grading, and the automated plagiarism checking. According to Baraishuk (2021) the application of AI in education affects three areas: Gathering data about every learner before starting the training. These data are compared with a model (competency matrix) to define the existing knowledge gaps for everyone individually. It enables the creation of a personalized learning path including only relevant topics to be learned instead of passing a generalized curriculum created for all learners. As a result, the learning process gets much faster. The learner's progress is automatically tracked during the training. It helps timely detect gaps in knowledge acquisition by using knowledge assessments created by AI. Also, it allows forecasting the learner's performance to get valuable insight for adjusting personal curriculum or timely intervening in the learning process (Baraishuk, 2021).

Further increasing the effectiveness of the training is achieved by creating a personalized learning path for every learner and its automated adjustments along the learning process based on regular AI-powered reassessments. The assessment in eLearning can also be integrated with AI which can lead to more customized learning by providing details of the progress of each learner (Cope & Kalantzis, 2019). "Ambient intelligence classroom" is a concept given by Montebello (2019) that can acquire student information through motion detectors, eye-trackers, keystroke counts, click-stream records, and engagement logs.

Personal learning network (PLN) Arsarkij & Laohajaratsang (2021) explain that from numbers of the theoretical reviews, the four components of PLN are: (1) learning resources, which include information, people, and networks; (2) learning tools, which are the devices, applications, platforms or networks; (3) learning content which means any kind of knowledge content, particular subject contents, or any area of interest that learners study, and; (4) learning activities, defined as the activities or processes that learners perform in order to gain knowledge or to contribute knowledge. Personal learning networks are traditionally considered to encompass the online communities' learners are registered with, and with whom they engage with to contribute and exchange information (Leone, 2013 in Montebello, 2016).

H5a. Perception of learners about personal learning network (PLN) enabled by AI affects the perceived ease of use for eLearning.

H5b. Perception of learners about PLN enabled by AI affects the perceived effectiveness of eLearning.

H5c. Perception of learners about PLN enabled by AI affects perceived usefulness for eLearning.

H5d. Perception of learners about PLN enabled by AI affects attitude for eLearning.

H5e. Perception of learners about PLN enabled by AI affects satisfaction for eLearning.

H5f. The relationship between PLN and attitude for eLearning is mediated by perceived ease of use, perceived effectiveness and perceived usefulness.

H5g. The relationship between PLN and satisfaction for eLearning is mediated by perceived ease of use, perceived effectiveness and perceived usefulness.

Personal Learning Profile (PLP): Daunert & Price (2014) suggest that, personal learning portfolios are "practical tools for supporting self-directed and reflective learning". They also state that portfolios also support collaborative learning whereby learners share their work and resources for educational purposes. Montebello (2016) describe that such profiles represent a direct mapping to the distinctive characteristics of individual user as they differ in their academic background, interests, preferences, and learning goals. The user could be initially asked to explicitly declare the specific qualities, descriptions or characteristics that can be employed to develop his/her profile

H6a. Perception of learners about personal learning profile (PLP) enabled by AI affects the perceived ease of use for eLearning.

H6b. Perception of learners about personal learning profile (PLP) enabled by AI affects the perceived effectiveness of eLearning.

H6c. Perception of learners about personal learning profile (PLP) enabled by AI affects perceived usefulness for eLearning.

H6d. Perception of learners about PLP enabled by AI affects attitude for eLearning.

H6e. Perception of learners about PLP enabled by AI affects satisfaction for eLearning.

H6f. The relationship between personal learning profile PLP and attitude for eLearning is mediated by perceived ease of use, perceived effectiveness and perceived usefulness.

H6g. The relationship between personal learning profile PLP and satisfaction for eLearning is mediated by perceived ease of use, perceived effectiveness and perceived usefulness.

Personal Learning Environment (PLE) The Personal Learning Environment (PLE) is the combination of tools, people, and services that make up individualized resources and approaches to learning. It's centered around the individual's efforts to learn. The PLE may include course resources, such as information from the lectures and assignments that happen in the classroom, online lessons or hybrid lessons. When it's well designed, the PLE will connect the user the people and information that are the most useful and will make the user feel like a team is working together. The PLE is someone's personal resource for answers to questions, supporting context for ideas, and illustrations of the way concepts work (https://study.com/academy).

H7a. Perception of learners about PLE enabled by AI affects the perceived ease of use for eLearning.

H7b. Perception of learners about PLE enabled by AI affects the f perceived effectiveness of eLearning.

H7c. Perception of learners about PLE enabled by AI affects perceived usefulness for eLearning.

H6d. Perception of learners about PLE enabled by AI affects attitude for eLearning.

H6e. Perception of learners about PLE enabled by AI affects satisfaction for eLearning.

H7f. The relationship between PLE and attitude toward eLearning is mediated by perceived ease of use, perceived effectiveness and perceived usefulness.

H7g. The relationship between PLE and satisfaction for eLearning is mediated by perceived ease of use, perceived effectiveness and perceived usefulness.

All the above hypotheses can be presented in the following Figure 2 where PLE, PLP and PLN, enhanced by AI, will influence the PEOU, PE and PU of the Greek woman. Further, PEOU, PE and PU will impact Greek woman's ATT and S and bust the woman's intention to use eLearning. The mediation effect of PEOU, PE and PU between PLE, PLN and PLP and ATT and S can also be described in the theoretical model in Figure 2.

RESEARCH MODEL

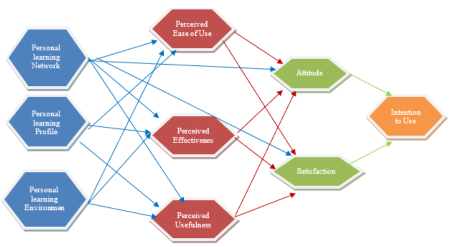

Figure 2

METHODOLOGY

The data of this research was collected from Greek women who were working professionals and students and have used an eLearning platform. The questionnaire that captured women's perception regarding AI-enabled eLearning module was the same used in Kashive's et al (2020) article "Understanding user perception toward artificial intelligence (AI) enabled eLearning". Responses were received from 120 women, and 63% were students while 35% were working professional.

The maximum age group represented was between 21 and 34 years. As for their age, 55,8% belonged to the junior level, 28,3% from the middle level and 15,8% from a senior level. From working professionals, 9, 6% belonged to the junior level, 50% to the middle level and 40,4 % to a senior level.

As can be seen in Figure 2, structure equation modeling (SEM) is using smart Partial Least Square. Smart PLS was used for model building and model path and hypothesis were tested to look into the causal relations between the variables (Urbach & Ahlemann, 2010). This approach is variance-based and does not need normalization as in the case of covariance-based approach and is good for the small sample calculated by the minimum R-square method where theory building is an attempt by the research (Hair et al.,2014). The common method bias was checked through Herman's single factor test and results were quite satisfactory, the research does not suffer from common method bias, as items did not load on a single factor.

Perceived ease of use (PEOU), perceived usefulness (PU), and attitude towards behavioral intention were adapted from the TAM model (Davies, 1989). PLP, PLN, and PLE scale PEOU, PU, and attitude scale, user satisfaction and behavioral intention to use were adopted from the scale used by Kashive et al. (2020) study which was based on the book 'AI Injected eLearning: The future of online education by Montebello (2017). PLP was measured through four items, PLN with three items and PLE with two items.

As seen in Figure 3, the PLS-SEM model was created, and confirmatory factor analysis was conducted, and all the loading on latent variables greater than 0.70 were taken. No item was dropped as all showed high loading on their respective variable. The reliability and validity were tested for model assessment, and reliability values of more than 0.80 were accepted. As seen in Table 1, the construct's composite reliability was higher than 0.790, and the construct convergent validity, i.e. average variance extracted (AVE), was higher than 0.5 (Hair et al., 2014). The discriminate validity was also tested as the square root of AVE values was higher than the inter-construct correlations, and all indicators loading were higher than their respective cross-loadings, as seen in Table 2 (analysis according to Kashive et al., 2020).

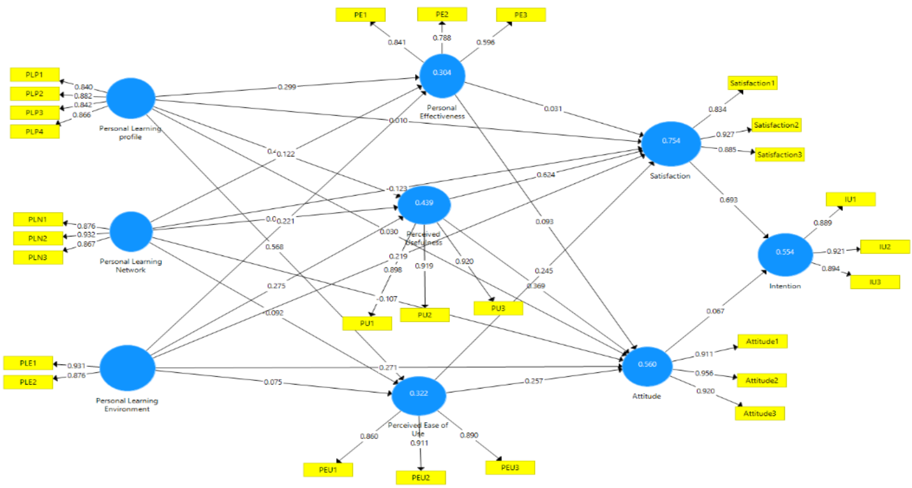

Figure3- PLS-SEM diagram

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Attitude	0.920	0.921	0.950	0.863
Intention	0.885	0.890	0.929	0.813
Perceived Ease of Use	0.865	0.870	0.917	0.787
Perceived Usefulness	0.899	0.899	0.937	0.832
Personal Effectiveness	0.608	0.655	0.790	0.561
Personal Learning Environment	0.780	0.824	0.899	0.817
Personal Learning Network	0.871	0.881	0.921	0.796
Personal Learning profile	0.880	0.883	0.918	0.736
Satisfaction	0.858	0.869	0.913	0.779

Table 1- Construct reliability and validity

	Attitude	Intention	Perceived Ease of Use	Perceived Usefulness	Perceived Effectiveness	Personal Learning Environment	Personal Learning Network	Personal Learning Profile	Sati-sfaction
Attitude	0.929								
Intention	0.591	0.902							
Perceived Ease of Use	0.529	0.442	0.887						
Perceived Usefulness	0.652	0.639	0.389	0.912					
Perceived Effectiveness	0.552	0.481	0.457	0.658	0.749				
Personal Learning Environment	0.565	0.486	0.355	0.560	0.474	0.904			
Personal Learning Network	0.348	0.329	0.260	0.451	0.419	0.614	0.892		
Personal Learning Profile	0.551	0.486	0.563	0.615	0.496	0.594	0.539	0.858	
Satisfaction	0.756	0.743	0.554	0.813	0.611	0.601	0.375	0.611	0.882

Table 2- Discriminate validity

The structural model assessments showed the path coefficients when non-parametric boot strapping was applied, as shown in Table 3. It was seen that the perceived ease of use and perceived usefulness showed a significant effect on both attitude and satisfaction as p-values are 0.007, 0.00, 0.00, 0.00<0.05 at 95% significant level (H1a, H1b, H2a, and H2b both supported). Perceived effectiveness did not impact attitude and satisfaction as p-values are 0.362, 0.667 > 0.05 at 95% significant level (H3a and H3b not supported). At last, only satisfaction impacted intention to use eLearning p-values is 0.00 < 0.05 at 95% significant level (H4b supported) and not attitude as p-value is 0.503> 0.05 at 95% significant level (H4a not supported). After the PLN was tested, it did not impact perceived ease of use, perceived effectiveness and perceived usefulness, attitude p-values are 0.393, 0.237 and 0.539 0.285> 0.05 at 95% significant level (H5a, H5b, H5c all not supported) but only PLN impacted satisfaction as p-value is 0.042<0.05 at 95% significant level (H5d supported) and not attitude (H5e not supported).

For the PLP, it was seen that it impacted perceived ease of use, perceived usefulness and perceived effectiveness p-values was 0.00, 0.00, 0.016 < 0.05 at 95 % significant level (H6a, H6b, H6c were supported). PLP did not impact attitude and satisfaction as p-values are 0.784, 0.880>0.05 at 95% significant level. (H6d, H6e not supported).

PLE impacted perceived usefulness, p-values are 0.006< 0.05 at 95% significant level but not perceived ease of use and perceived effectiveness p-values are 0.605 and 0.059> 0.05 at 95% significant level (H7c were supported but not H7a and H7b). PLE impacted attitude and satisfaction as p-values are 0.007, 0.010<0.05 at 95% significant level. (H7d, H7e supported). When testing for the direct effect of all three components (PLE, PLP and PLN) with attitude and satisfaction, only personal learning network (PLN) showed a significant relationship with satisfaction at a 90% sig level and personal learning environment (PLE) with attitude and satisfaction.

The R-square values give the endogenous construct predictive power and provide the % of variance explained by a particular variable. The R-square value were perceived ease of use (0.322), perceived effectiveness (0.304), perceived usefulness (0.439), attitude (0.560), satisfaction (0.754) and intention (0.554).The attitude can be explained to 56% and satisfaction to 75.4% by the variable considered. Finally, the intention % variance explained was 55.4%.

	Original Sample (O)	*p*Values	Decision p <=0,05
Attitude -> Intention	0.067	0.503	Not accepted
Perceived Ease of Use -> Attitude	0.257	0.007	*Accepted*
Perceived Ease of Use -> Satisfaction	0.245	0.000	*Accepted*
Perceived Usefulness -> Attitude	0.369	0.000	*Accepted*
Perceived Usefulness -> Satisfaction	0.624	0.000	*Accepted*
Personal Effectiveness -> Attitude	0.093	0.362	Not accepted
Personal Effectiveness -> Satisfaction	0.031	0.667	Not accepted
Personal Learning Environment -> Attitude	0.271	0.007	*Accepted*
Personal Learning Environment -> Perceived Ease of Use	0.075	0.605	Not accepted
Personal Learning Environment -> Perceived Usefulness	0.275	0.006	*Accepted*
Personal Learning Environment -> Perceived Effectiveness	0.221	0.059	Not accepted
Personal Learning Environment -> Satisfaction	0.219	0.010	*Accepted*
Personal Learning Network -> Attitude	-0.107	0.285	Not accepted
Personal Learning Network -> Perceived Ease of Use	-0.092	0.393	Not accepted
Personal Learning Network -> Perceived Usefulness	0.054	0.539	Not accepted
Personal Learning Network -> Perceived Effectiveness	0.122	0.237	Not accepted
Personal Learning Network -> Satisfaction	-0.123	0.042	*Accepted*
Personal Learning profile -> Attitude	0.030	0.784	Not accepted
Personal Learning profile -> Perceived Ease of Use	0.568	0.000	*Accepted*
Personal Learning profile -> Perceived Usefulness	0.423	0.000	*Accepted*
Personal Learning profile -> Perceived Effectiveness	0.299	0.016	*Accepted*
Personal Learning profile -> Satisfaction	0.010	0.880	*Not accepted*
Satisfaction -> Intention	0.693	0.000	*Accepted*

Table 3- Path coefficient for direct effect

Mediation Analysis

In Table 4 path coefficients for specific indirect effect are presented. Mediation analysis was conducted through bootstrapping.

It was PU mediated between PLE and user Attitude as well as PLE and overall Satisfaction. Hence H7f and H7g were supported.

It was seen that PU and PEOU mediated between PLP and user Attitude. Hence the H6fd of the research was supported and the H6e was not supported.

PLN was not mediated by PEOU, PE and PU to user Attitude and Satisfaction. Hence H5f and H5g were supported.

As for the users satisfaction also showed a mediation effect between PLE and Intention. Satisfaction also showed a mediation effect between PEOU, PU and Intention.

The specific indirect effect is shown in Table 4 for those which are having p-values significant at 95 % sig level. As zero does not fall in the bias-corrected upper level and lower level bootstrapped confidence intervals, the indirect effect is proved as seen in Table 4.

	p Values	Bias corrected CI 2.5%	Bias corrected CI 97.5%	Decision
Perceived Ease of Use-> Satisfaction -> Intention	0.001	0.082	0.271	Supported
Personal Learning Environment -> Perceived Usefulness -> Attitude	0.040	0.028	0.219	Supported
Personal Learning Environment -> Perceived Usefulness -> Satisfaction	0.012	0.058	0.325	Supported
Personal Learning Environment -> Perceived Usefulness -> Satisfaction -> Intention	0.026	0.038	0.242	Supported
Personal Learning Environment -> Satisfaction -> Intention	0.018	0.030	0.282	Supported
Personal Learning Profile -> Perceived Ease of Use -> Attitude	0.009	0.042	0.260	Supported
Personal Learning Profile -> Perceived Ease of Use -> Satisfaction -> Intention	0.001	0.046	0.160	Supported
Personal Learning Profile -> Perceived Usefulness -> Attitude	0.004	0.069	0.297	Supported

Table 4- Path coefficients for specific indirect effect

As seen in Table 5, attitude (A) impacted the intention (I) to use eLearning more in students than in working professionals as the difference in path value was 0.120. Also, it was seen that satisfaction (S) impacted the intention (I) to use eLearning more in students than in working professionals as the difference in path coefficient was 0.066.

It was seen that personal learning environment (PLE) impacted attitude (A), satisfaction (S), to eLearning more in working professionals than in students as the difference in path values were respectively -0.077 and -0.124. Also the personal learning profile (PLP) impacted attitude to eLearning more in working professionals than in students as the difference in path values was -0.072. On the other hand personal learning network (PLN) impacted attitude (A), satisfaction (S), to eLearning more in students than working professionals as the difference in path values were respectively +0.043 and +0.150 and personal learning profile (PLP) impacted satisfaction to eLearning more in students than working professionals as the difference in path values were respectively +0.010.

	Path Coefficients-diff (Student vs Working)	p-Value original 1-tailed (Student vs Working)	p-Value new (Student vs Working)
Attitude -> Intention	0.120	0.298	0.596
Perceived Ease of Use -> Attitude	0.234	0.163	0.327
Perceived Ease of Use -> Satisfaction	-0.188	0.862	0.276
Perceived Usefulness -> Attitude	-0.014	0.534	0.932
Perceived Usefulness -> Satisfaction	0.029	0.418	0.835
Personal Effectiveness -> Attitude	0.034	0.439	0.878
Personal Effectiveness -> Satisfaction	0.123	0.242	0.484
Personal Learning Environment -> Attitude	-0.077	0.634	0.732
Personal Learning Environment -> Perceived Ease of Use	-0.329	0.916	0.168
Personal Learning Environment -> Perceived Usefulness	-0.303	0.845	0.311
Personal Learning Environment -> Perceived Effectiveness	-0.267	0.800	0.400
Personal Learning Environment -> Satisfaction	-0.124	0.725	0.549
Personal Learning Network -> Attitude	0.043	0.414	0.828
Personal Learning Network -> Perceived Ease of Use	0.102	0.319	0.638
Personal Learning Network -> Perceived Usefulness	-0.140	0.714	0.572
Personal Learning Network -> Perceived Effectiveness	0.024	0.463	0.926
Personal Learning Network -> Satisfaction	0.150	0.212	0.424

Personal Learning Profile -> Attitude	-0.072	0.619	0.762
Personal Learning Profile -> Perceived Ease of Use	0.195	0.153	0.306
Personal Learning profile -> Perceived Usefulness	0.047	0.396	0.793
Personal Learning profile -> Perceived Effectiveness	-0.136	0.689	0.621
Personal Learning profile -> Satisfaction	0.010	0.487	0.973
Satisfaction -> Intention	0.066	0.354	0.707

Table 5- Multigroup analysis for types of learner

DISCUSSION

Bouchrika (2022) argues that as online learning becomes the new norm amid the COVID-19 pandemic, many colleges and universities are abruptly adopting the technology in place of the traditional classroom setting. In this it can be added that eLearning and learning management systems have changed also the environment of labour market. However, one important factor affecting the efficacy of eLearning materials is the educator's and learner's readiness for online learning. When users feel that they are ready for online education, training, working online they are more encouraged to complete online courses or their jobs and are more likely to reap the maximum benefits of eLearning. Access to a reliable and stable Internet connection is essential. However, the fact that Internet access varies for each individual living in different regions and countries is creating a digital divide affecting the effectiveness of online learning across the globe.

This research detects users' approach of PLP, PLN and PLE and their effect on various aspects of learning. The researcher has used a small sample so the use of Smart-PLS SEM method was more convenient for giving results.

The results of this research show that PLE impacted PU, but not PEOU and PE. Hence this give us the motive to think that the user needs an autonomous and positive space to work and receive satisfaction from the results so that he/she can continue to work in this way as eLearning, online working have to overcome the traditional ways of learning and working which are deeply rooted in consciousness. Personal learning environment plays an essential role in deciding usefulness of learning by the e-learning module.

As for the PLP, it was seen that it impacted PEOU, PE and PU. In recent years, the use of artificial intelligence (AI) has brought many changes in various industries. The elearning industry is no exception. AI in the education sector has offered opportunities for adaptive learning features, improving learner experience, and providing more personalized learning content. This technology's impact is felt across all educational levels, from kindergarten through higher education. Its dynamic nature introduces smart learning content, such as customized learning digital interfaces and digitized textbook guides. AI is also used to support individualized tutoring and instruction in classrooms (Bouchrika, 2022). AI techniques can look into the profile of learner and suggest the module matching more with the individual learner, and this will lead to increased perceived effectiveness and satisfaction with e-learning (Kashive et al., 2020) After the PLN was tested, the result is that did not impact PEOU, PE and PU.

Finally, the research has shown that PEOU showed a mediating effect between PLP and ATT and S, PU mediates between ATT and PLP. Further S mediates between PEOU and I. Additionally the research has shown that PU showed a mediating effect between PLE and ATT and S and finally I, Further S mediates between PU and I. Hence, the intention to use any e-learning system is influenced by the women's satisfaction level and how they find convenience to its use. When testing for the direct effect of all three components (PLE, PLP and PLN) with attitude and satisfaction, only personal learning network (PLN) showed a significant relationship with satisfaction and personal learning environment (PLE) with attitude and satisfaction. PLP did not impact directly attitude and satisfaction.

In the multigroup analysis attitude's (A) and satisfaction's (S) impact to the intention to use eLearning differ across the two groups of women as it affects more in students than in working professionals. In the same analysis it was seen that personal learning environment (PLE) impacted attitude (A), and satisfaction (S) to eLearning differently in the two categories of women, precisely more in working professionals than in students. On the other hand, personal learning network (PLN) impacted attitude (A) and satisfaction (S), to eLearning more in students than working professionals. Also the personal learning profile (PLP) impacted attitude to eLearning more in working professionals than in students and personal learning profile (PLP) impacted satisfaction to eLearning more in students than working professionals

CONCLUSION

A diversity among the two groups of women is detected and in this case the involvement of A.I. and eLearning can be the solution to understand the women's profiles and offer them the right context of continuous learning as A.I. can be adaptive and matching the profile of the learner and produce more personalized learning content.

Although in this study, PLN has not come significant with women's PE, PEOU, PU, future research should look into it. This variance is significant as it includes learning resources like information, people, and networks, learning tools, learning content and learning activities. Additionally, to the above research there is a need of a research with a broader sample of women with more demographic characteristics to be taken into account.

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