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E-learning system usage continuance intention of adult learners: A data mining approach

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Abstract

The purpose of this study is to ascertain the variables that influence adult learners' continuing use of online learning environments. The participants were 307 Turkish students of a non-thesis masters' in a distance education program. The J48 algorithm in WEKA data mining software were used to analyse the data. As a result of the research, it was determined that variables such as perceived value, system quality, confirmation, and age did not have a significant effect on the intention to use the online learning system, while satisfaction, perceived usability, utilitarian value, information quality, outcome expectations, and service quality did. This finding indicates the importance of emotion generated by their interaction with the e-learning system, adult learners' self-development expectations, usability characteristics of the e-learning system, information and service quality, and outcome expectations. The TAM, ECM, Updated IS, model, SDT, SCT all of appear to be significant predictors of adult learners' continuance intentions. This result reveals that lifelong learners' personal development expectation, the emotion generated as a result of their interaction with the e-learning system and the user-oriented design of the e-learning system are important. In other words, it is concluded that the intersection of instructional design, information technologies and marketing disciplines is important in predicting lifelong learners' intention to use e-learning systems regardless of age or gender.

Keywords: e-learning system usage, continuance intention, adult learners, data mining.

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Introduction

The rapid advances in information and communication technology have altered the amount of information produced, the methods of instruction, the nature of professions, and the way we work. This transformation has been expedited by the pandemic. As a consequence, it has begun to exert a greater influence on business and education systems. However, as Dhawan (2020) stated, while technology can assist in overcoming some barriers, we must be extremely prepared to rapidly adjust to mandatory changes like e-learning in pandemic scenarios such as COVID-19.

After the pandemic, it is expected that interest in e-learning will continue to grow. According to Almaiah, Al-Khasawneh, and Althunibat (2020), having sufficient computer skills and a positive attitude toward interacting with the e-learning system at this time will facilitate the e-learning system's successful adoption. On the other hand, Pant (2014) underlines potential challenges such as individual differences among learners in e-learning, a lack of feedback, inadequacy of social contact, and insufficiency of support and services in content creation. Similarly, Kebritci, Lipschuetz, and Santiague (2017) classify difficulties into student, teacher, and content categories. Aini, Budiarto, Putra, and Rajharda (2020) classified the challenges encountered by students in online learning during the epidemic into three categories. The first theme is internet connectivity issues. The second theme describes the support that e-learning technologies provide. The ease of use, technical support, and accessibility are all examples of these services. The final theme is self-regulation difficulties, such as low motivation.

Almaiah, Al-Khasawneh, and Althunibat (2020) identify the factors affecting the adoption of e-learning systems during a pandemic as technology, the quality of the e-learning system, culture, self-efficacy, and trust. One of the critical variables affecting students' adoption of the e-learning system is their culture. Self-efficacy is another concept being considered. Additionally, universities should have an e-learning system that is both secure and reliable. The trust factor is strongly influenced by the security characteristics of the e-learning system. The technological dimension is defined by the systems that comprise the e-learning system's infrastructure. Efficiency, usefulness, ease of use, reliability, and content design are all sub-dimensions of the technological dimension. It is stated that the primary factor is the quality of the e-learning system, followed by the usability.

Ferri, Grifoni, and Guzzo (2020) categorize the e-learning problems encountered during the pandemic phase as technological, pedagogical, and social. Technological challenges stem from students' lack of requisite equipment and internet connectivity issues. Pedagogical challenges manifest as a lack of digital skills, an inability to organize content appropriately, a lack of interaction and motivation, and a lack of social presence. Social difficulties are caused by a lack of student-teacher and student-student interaction.

Not only did e-learning play a critical role during the pandemic, but it also provided critical chances for lifelong learning (Thorpe, 2005). The time and location flexibility offered by e-learning contribute significantly to the development of individuals who continue to work. Adults now have opportunities to develop themselves through e-learning while managing work and family life. However, it is believed that the expectations of adults who have not encountered e-learning during their early educational experiences, as well as the difficulties they would face as a result of e-learning activities, may differ from those of today's students. Therefore, it is critical to understand the factors that influence adult learners' intention to use e-learning systems when adjusting to the information age. The purpose of this research is to determine the variables that indicate adult learners' continued use of online learning environments.

Theoretical Background

Adult Education

Adult education has become an important aspect of lifelong learning and professional development. One of the most well-known is the andragogy theory, which suggests that adult learners have different learning needs and preferences than children and should be treated accordingly (Knowles, Holton, & Swanson, 2015). According to Knowles (1980), adult education is a process of self-directed learning that allows adults to acquire knowledge, skills, and attitudes relevant to their lives. The concept of andragogy is closely associated with adult education. It emphasizes the need for adults to be involved in their own learning process and the importance of relevance and problem-centeredness in the learning experience (Knowles, 1980). The field of adult education is constantly evolving, and several trends have emerged in recent years. One significant trend is the increasing use of technology in adult education. Online learning, webinars, and other e-learning platforms are becoming more popular, and they provide adults with flexibility and convenience (Garrison & Kanuka, 2004). As more and more adults engage in lifelong learning activities, the need for research on the effectiveness of adult learning programs has become increasingly important. Several factors can impact the effectiveness of adult learning programs. One important factor is prior knowledge and experience, as adult learners often bring a wealth of experience to the learning process (Merriam, Caffarella, & Baumgartner, 2007). Another important factor is motivation, as adult learners are often motivated by different factors than children, such as career advancement or personal growth (Zimmerman, 2008). There are several strategies that have been shown to be effective in promoting adult learning. One important strategy is to create a supportive learning environment that encourages participation and collaboration (Merriam, Caffarella, & Baumgartner, 2007). Another strategy is to incorporate real-world examples and problem-solving activities into the learning process (Wlodkowski & Ginsberg, 2010). Hence, adult learning is a multi - dimensional process including a variety of circumstances and perspectives. While much has been achieved in comprehending adult learning, there is still a great deal to learn about how to support adult learning efficiently. Educators can build more successful and engaging programs for adult learners if they continue to perform research in this field.

Online Learning Continuance

There are numerous models or theories that explain how an information system is utilized. According to Islam (2011), the process that began in the 1970s with research to explain consumer purchasing behavior continues now in other domains. The use of instant messaging software (Oghuma et al., 2016), public transit (Fu, Zhang & Chan, 2018) or social networking sites (Hasan, 2019) can be given as examples. When the theories and models in the literature are examined, Expectancy disconfirmation theory (EDT) (Oliver, 1980) attempts to establish a relationship between expectation, disconfirmation, satisfaction, attitude, and purchase intention. To establish the aforementioned relationship, a model was provided that included expectation, perceived performance, disconfirmation, and satisfaction constructs. The model depend on the notion of expectation as a mediator for consumer satisfaction and disconfirmation of the expectation. Furthermore, there is an argument that consumer satisfaction has an effect on attitude shifts and purchase decisions. According to Grimmelikhuijsen and Porumbescu (2017), the model posits that satisfaction is not solely a function of a government service's objective performance, but also of implicit expectations about the service's previous performance. When a service's perceived performance exceeds that of the preceding service, it has a favorable effect on disapproval and citizen satisfaction. Although the model is widely accepted for evaluating satisfaction with public services (Van Ryzen, 2006), aspects of the model's basic premises are challenged, and the necessity of exploring the relationship between cognitive biases and satisfaction is underlined (Grimmelikhuijsen & Porumbescu, 2017).

Based on the EDT, Bhattacherjee (2001) applied the expectation confirmation model (ECT) to investigate the influence of cognitive beliefs on the intention to continue using information systems. The consumer behavior literature played a significant role in the model's development. The model is composed of the following factors: confirmation, perceived usefulness, satisfaction, and the intention to continue using the IS. According to ECT, the intention of users to continue using information systems (IS) is driven by their satisfaction with previous IS use. Confirmation and perceived usefulness are two characteristics that predict satisfaction. Bhattacherjee, Perols, and Sanford (2008) defined the model's expanded version as comprising the following factors: disconfirmation, satisfaction, post-usage usefulness, IT self-efficacy, continuance intention, facilitating conditions, and continuance behavior.

Another model that is frequently used in the literature is the Technology acceptance model (TAM). Davis (1989) asserts that the instruments used to predict users' acceptance of computers are subjective. Because of this, he asserts that the data gathered via the use of the aforementioned methods is insufficient to explain the relationship with system use. In this regard, he added two variables as primary predictors of user acceptance in his model. These are the variables known as perceived usefulness and perceived ease of use. Following the model's introduction, it frequently found a place in the literature with new additions (Sumak, Hericko & Pusnik, 2011). Venkatesh and Davis (2000) extended the model by including social influence processes (subjective norms, voluntarism, and image) as well as cognitive instrumental processes (job interest, output quality, provability of outputs, and perceived ease of use). Finally, Venkatesh and Bala (2008) included the predictors of ease of use, computer self-efficacy, external control perceptions, computer anxiety, computer playfulness, perceived enjoyment, and objective usability.

According to Delone and McLean (1992), defining the independent factors needed to predict the effectiveness of information systems is difficult. They propose IS success model to establish the technical, semantic, and efficacy levels for evaluating an information system's output. They then developed a taxonomy comprised of system quality, information quality, usability, user satisfaction, individual impact, and organizational impact. DeLone and McLean (2003) did not include individual and organizational effect variables in their update of the IS model, but did include service quality, intention to use, and net benefits variables.

Liao, Palvia, and Chen (2009) used multiple group analysis to assess Davis's (1989), Bhattacherjee's (2001), and Oliver's (1980) models. They assert that each model has a different explanatory capacity as a result of its differing assumptions about how users behave. As a result, they established the technology continuance model (TCT) model for short and long-term users by utilizing the six structures in the three models under discussion. The model is composed of the following factors: perceived ease of use, perceived usefulness, confirmation, attitude, satisfaction, and the intention to continue using IS. They assert that the new model's most significant contribution to the literature is its integration of attitude and satisfaction structures into a single model.

Venkatesh, Morris, Davis, and Davis (2003) focused on the theory of reasoned action (TRA), the technology acceptance model (TAM), the motivational model, the theory of planned behavior, the model of personal computer use, the innovation diffusion theory, and the social cognitive theory models. Then, these models were experimentally compared, and the Unified theory of acceptance and the use of technology (UTAUT) model was developed by combining the conceptual and experimental similarities. Performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and use behavior are the factors in the UTAUT model. Additionally, the model incorporates essential characteristics such as gender, age, experience, and voluntariness. The UTAUT model, it is argued, encompasses the explanatory power and moderator effects of the other models.

The literature also includes variables that affect the use of e-learning systems but are not included in the aforementioned models. Some of them are: system use, distributive fairness, procedural fairness, interactional fairness (Chiu, Chiu, & Chang, 2007), perceived usefulness (Hsu & Chiu, 2004), perceived value (Chang, Hsu, Hsu & Cheng, 2014), perceived usability, perceived quality, and perceived value (Chiu, Hsu, Sun, Lin, & Sun, 2005), and perceived self-efficacy (Liaw & Huang, 2013).

Methodology

The purpose of this research is to determine the variables that indicate non-thesis master's students' continued use of online learning environments based on Daghan and Akkoyunlu' s (2016) model. When the researches in the literature are reviewed (Cheng, 2019; Al Amin, Razib Alam, & Alam, 2023), it is noticeable that the structural equation model is used to analyze the majority of them. In this context, data mining techniques were employed to add a new perspective to the literature. The model's hierarchical structure was validated using the J48, Reptree, and RandomTree decision tree algorithms.

Participants

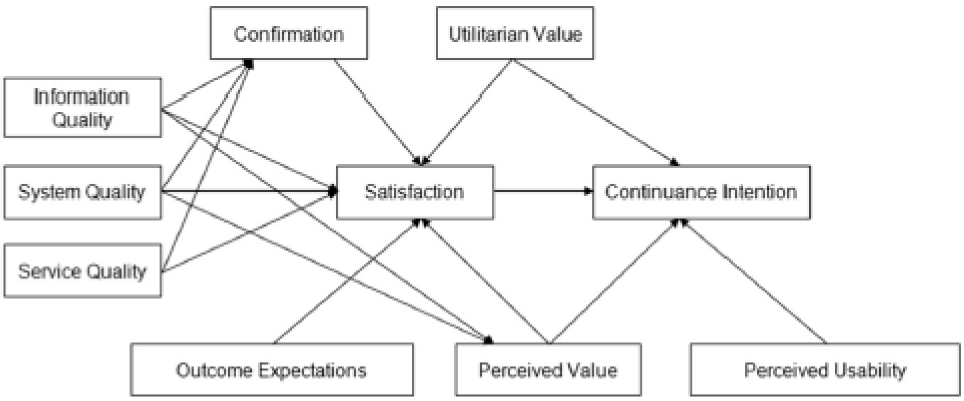
The research sample consists of students enrolled in a state university's Master's Program in Management Information Systems without a thesis in Turkey. Students enrolled in the program and enrolled in courses during the 2018-2019, 2019-2020, 2020-2021 and 2021-2022 academic years provided data. There were 57 female and 250 male participants. The age range is 23-62, with the average being 35. Five individuals reported that they were unemployed. The remaining 302 respondents indicated that they work in 19 diversified sectors (such as health, informatics, education, and service). According to participants' self-statements, 217 of them always followed the lessons, while 77 ones did regularly and 13 ones did sometimes.

Data Collection

Daghan and Akkoyunlu's (2016) model of online continuation usage intention was used to collect data for the research. Permissions were obtained for the use of the scale. The scale, which consisted of forty items, incorporated the ten factors. Factors are; information quality, system quality, service quality, confirmation, outcome expectations, perceived value, utilitarian value, perceived usability, satisfaction and continuance intention. The factors information quality, system quality, and service quality are adapted from DeLone and McLean's (2003) updated information systems success model. The factors satisfaction, confirmation, and intention to continue are extracted from the ECM (Bhattacherjee, 2001), the Cognitive model (Oliver, 1980), and the TCT (Liao, Palvia & Chen, 2009). The outcome expectations, perceived value, utilitarian value, and perceived usability are all based on research that produces relevant results in the literature (Chiu, Sun, Sun, & Ju, 2007; Kim & Oh, 2011; Hsu, Chiu & Ju, 2004; Chang, 2013; Chiu, Hsu, Sun, Lin, & Sun, 2005; Liao, Palvia, & Chen, 2009). Figure 1 illustrates the Daghan and Akkoyunlu's (2016) model.

Figure 1

Continuance usage intention of online learning environments



Data Analysis

Primarily, the continuance intention factor was converted from continuous to categorical data in order to determine the variables that predict continued use in online learning environments. The data below the average were classified as low, while the data above the average were classified as high. Then, J48, RepTree, and RandomTree decision tree algorithms under WEKA data mining software are used to analyse. Cross-validation is set to 10 in the analysis process, the percentage split is set to 66 percent, and the minnumobj value is set to 2.

Results

Table 1 and Table 2 include the findings of the data mining analysis conducted to ascertain the variables that indicate continuance use in online learning environments. The analysis's independent

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variables are gender, age, and aspects of the online learning model's intention to continue using it. The dimensions of the model are confirmation (conf), outcome expectations (out), utilitarian value (util), perceived value (val), perceived usability (usa), satisfaction (sat), and continuance intention. Table 1 summarizes the reliability values for the analyses done using the J48, RepTree, and RandomTree algorithms.

Table 1

Reliability values

Method	Results		
	J48	Reptree	RandomTree
Correctly Classified Instances	276	276	272
Correctly Classified Rate	89.920	89.902	88.599
Kappa statistic	0.798	0.797	0.772
Mean absolute error	0.116	0.143	0.114
Root mean squared error	0.304	0.294	0.321
Relative absolute error	23.219 %	30.569 %	22.760 %
Root relative squared error	60.955 %	58.963 %	64.186 %
Total Number of Instances	307	307	307

When the reliability values in Table 1 are checked, it becomes apparent that the J48 method produces more accurate results, albeit with minor differences. In determining the J48 algorithm's intention to use an e-learning system, 276 students out of 307 were correctly classified, providing an accuracy rate of 89.92 percent. Additionally, because the kappa coefficient is 0.798 and falls within the range of .61-.80, it is classified accurately (Landis & Koch, 1977). Following the reliability values, Table 2 contains the complete validity criteria for the classes.

Table 2

Validity criteria

	Class	TP rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
J48	Low	0.910	0.111	0.880	0.910	0.895	0.798	0.909	0.837
	High	0.889	0.090	0.917	0.889	0.903	0.798	0.909	0.909
	Weighted Avg.	0.899	0.100	0.900	0.899	0.899	0.798	0.909	0.875
Reptree	Low	0.897	0.099	0.890	0.897	0.893	0.798	0.934	0.918
	High	0.901	0.103	0.907	0.901	0.904	0.798	0.934	0.919
	Weighted Avg.	0.899	0.101	0.899	0.899	0.899	0.798	0.934	0.919
Random Tree	Low	0.903	0.130	0.862	0.903	0.882	0.773	0.904	0.857
	High	0.870	0.097	0.910	0.870	0.890	0.773	0.904	0.875
	Weighted Avg.	0.886	0.112	0.887	0.886	0.886	0.773	0.904	0.867

According to Table 2, it is clear that the J48 algorithm produces better results, although with minor differences in terms of reliability values. When classification results were analysed, the true positive rate average is 0.899, the false positive rate average is 0.100, the precision is 0.900, the recall is 0.899, the F-criterion is 0.899, the Matthew correlation coefficient is 0.798, the area under the ROC curve is 0.909, and the area under the precision-recall curve is 0.875. According to these statistics, the ROC area was decided to become the most essential performance criterion, while the FP ratio was determined to be the lowest rating. Figure 2 illustrates the decision tree structure formed by the J48 method.

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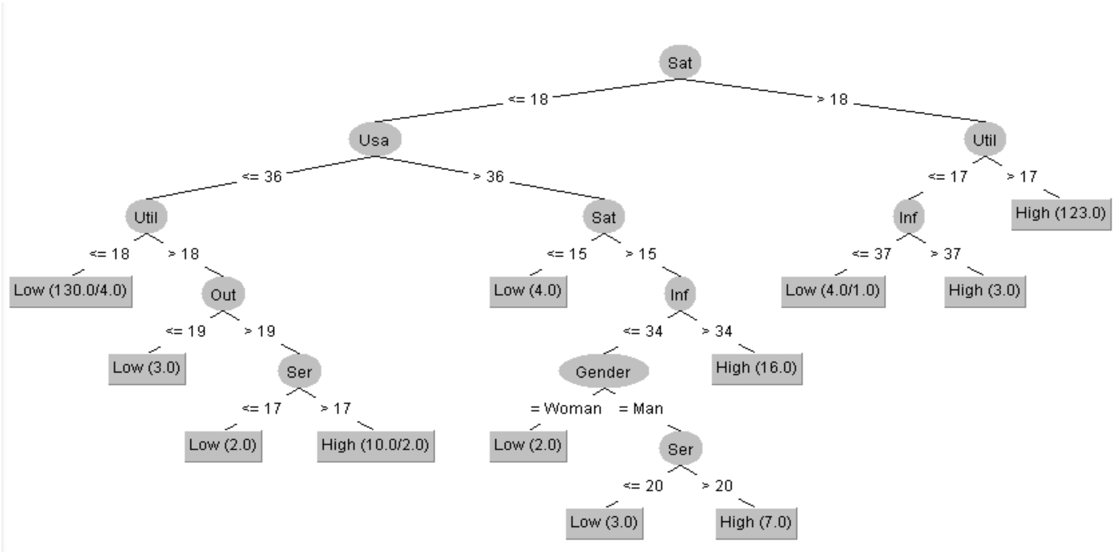
Figure 2

The decision tree of the J48 algorithm



When Figure 2 is analysed, decision tree has a six-level structure as a consequence of the study conducted to discover the factors that predict the intention to use online learning systems. The first level predictive variable is satisfaction. As a result, the cut-off point is determined to be 18 total points for the satisfaction sub-dimension. The utilitarian value is at the second level of the decision tree for learners with more than 18 points. The cut-off criterion for the utilitarian value variable is 17 points, and it is observed that participants with intentions to continue above 17 points have high intends to continue. 17 points and below is the information quality component that should be included in the decision tree framework. This factor has a cut-off score of 37. Participants with a total information quality factor score greater than 37 have high usage intentions, while those with a total information quality factor score of 37 or less have low continuance intentions.

For adult learners with a cut-off score of 18 or less on the satisfaction dimension, the perceived usability component is situated at the second level of the decision tree, with a cut-off score of 36. The satisfaction component regains significance for individuals with a cut-off score of 36, and it is observed that participants with a cut-off score of 15 and lower have low usage intentions. When it exceeds 15 cut-off points, the information quality element becomes more significant. While the intention to use is high above the 34 cut-off point, the gender element has an effect on those below. Women have a low intention to use, and service quality has a significant effect on intention to use, with a cut-off score of 20 in men.

At the second level of the decision tree, the perceived usability factor incorporates the utilitarian value factor with a cut-off score of 36 or less. A score of 18 or less suggests a low intention to use. If it is more than the cut-off value of 18, the dimension of outcome expectancy is included. Scores of 19 and below indicates a low intention to use, whilst scores over 17 service quality factor should be addressed. A cut-off score of 17 indicates a high intention to use, whereas a score of less than 17 suggests a low intention to use.

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Discussion

The research was conducted to determine the variables that predict non-thesis graduate students' continuance use of online learning environments. Data were analysed using machine learning techniques. The decision tree analysis performed using the J48 method reveals that the classification rate is 89.92 percent and that the classification is accurate when 0.798 kappa coefficient is considered. The satisfaction dimension is the first level variable that predicts intention to continue. The second level of the decision tree is devoted to perceived usability and utilitarian value. The third level repeats utilitarian value and satisfaction, whereas information quality is a new node. At the fourth level, outcome expectations are viewed as new nodes in the decision tree, while service quality and gender are viewed as new nodes at the fifth level. In other words, satisfaction, perceived usability and utilitarian value, the quality of content, outcome expectations, and service quality all have an effect on the desire to use e-learning systems. While satisfaction, information quality, and service quality are all based on a model, outcome expectancies, utilitarian value, and perceived usability are all based on studies that provide relevant findings in the literature.

According to Daghan and Akkoyunlu (2016), confirmation predicts satisfaction, and satisfaction predicts the intention to continue. Additionally, they assert that information quality, system quality, and service quality all have a substantial impact on confirmation and satisfaction. Similarly, Cheng (2020) asserts that university students' perceptions of interaction, course content, and course design all contribute significantly to their perceived usefulness, confirmation, and satisfaction in the cloud-based e-learning system, which results in their intention to continue either directly or indirectly. Confirmation has a considerable effect on satisfaction, according to Hayashi, Chen, Ryan, and Wu (2004) and Daneji, Ayub, and Khambari (2019). Meanwhile, satisfaction has a large impact on a student's intention to continue. Cheng and Yuen (2018) also examined the effect of satisfaction on LMS continuation intention in secondary schools and reached the same results. Similarly, as expected, satisfaction emerges as the most significant predictor variable for adult learners in this study. However, were not observed for the confirmation variable, which is critical for undergraduate students.

Oliver (1980) defines satisfaction as "a function of an initial reference point and some perceived deviation from it." as a consumer behaviour while Chiu, Sun, Sun, & Ju (2007) define it in the context of web-based learning as "an individual's feelings of pleasure or disappointment as a result of comparing the perceived performance (or outcome) of Web-based learning to his or her expectations." In this regard, the sense of dissatisfaction caused by the gap between adult learners' learning outcomes and expectations predicts their intention to use online learning systems significantly. In summary, satisfaction as a proxy for the intention to continue using an information system (Rahman, Zamri, & Eu, 2017) is reflected in the research findings.

According to Van Ryzen (2004), satisfaction is defined as an individual's summary evaluation regarding a product or service. From this vantage point, the components that comprise the contested decision take on greater significance. At the second level of the decision tree, these variables show as perceived usability and utilitarian value. Although neither variable is based on a theoretical model, they are critical for adult learners. Although utilitarian value is not based on a theory, Ryan and Deci (2000) assert that it can be advantageous as an extrinsic motivator. Chiu, Chiu, and Chang (2007) define utilitarian value as "the degree to which an activity is related to current and future goals, such as professional ambitions." This explanation encapsulates one of the primary expectations of adult learners regarding online education processes that contribute to their career goals. According to Kim and Oh (2011), utilitarian value influences not only continuing intentions, but also the acceptance of mobile data services. According to Zhou, Fang, Vogel, Jin, and Zhang (2012), numerous studies have underlined the effect of utilitarian value on satisfaction.

Perceived usability, another second-level characteristic, is described by the International Standards Organization as "a product or service that can be utilized effectively, efficiently, and satisfactorily by specified users in a stated context of usage." (International Standard ISO 9241-11, 1998). The concepts of effectiveness, efficiency, and satisfaction are highlighted in this definition. However, Chiu, Hsu, Sun, Lin, and Sun (2005) introduced the perceived usability element into the technological adoption model by including the compatibility variable alongside the usefulness and ease of use components (Davis, 1989). This finding is consistent with the findings of Bagci and Celik (2018), as well as Li and Yu (2020). In this context, adult learners place a premium on the e-learning system's usability aspects.

The decision tree's other layers contain variables relating to information quality, outcome expectations, and service quality. DeLone and McLean (1992) underlined thirty-four characteristics of the information quality factor, including correctness, relevance, and timeliness. DeLone and McLean (2003) defined service quality in terms of five dimensions: tangible, dependability, responsiveness, assurance, and empathy. In summary, it expresses the system's support for end users in terms of service quality. The information quality criterion is concerned with the anticipated characteristics of the information delivered as a product. According to DeLone and McLean (2003), the most critical quality component for determining the success of a single system is information quality or system quality. In comparison to separate systems, however, "quality of service" may be the most relevant metric for determining overall performance. The research findings corroborate this idea. As a result, the quality of information offered by an e-learning system to adult learners and the level of end-user support have a substantial impact on the desire to continue. A comparable outcome exists for factors relating to information quality, system quality, and service quality. Despite researches stressing the positive effect of system quality, information quality, and service quality on the use and satisfaction of distance education systems (Machado-Da-Silva, Meirelles, Filenga & Filho, 2014; Chopra, Madan, Jaisingh & Bhaskar, 2019), only information quality and service quality addressed in the decision tree. Additionally, age had no significant effect on the intention to use distance education systems. This conclusion is consistent with Almahamid and Rub's findings (2011). However, according to Shahzad, Hassan, Aremu, Hussein, and Lodhi's (2020) research comparing women and men's use of an e-learning portal, the quality of information and system quality have a greater effect on men's satisfaction. On the other hand, service and information quality have a positive effect on women’s satisfaction. Gender made a difference for learners at the fifth level of the decision tree, although only slightly below the cut-off score for the information quality component.

In Bandura's (1999) social cognition theory, outcome expectancies are another variable in the decision tree. They are one of the personal elements that influence an individual's behaviour (SCT). Individuals modify their conduct in part in response to their outcome expectations. We perform behaviours that are likely to yield pleasant outcomes; we do not perform behaviours that are unsatisfying or have punitive repercussions. As a result of environmental events, behaviours, and outputs, people develop outcome expectations. While Fasbender (2020) categorizes result expectancies into three dimensions: valence, temporal proximity, and region of repercussions, Chang, Liu, and Chen (2014) define them as utilitarian or hedonic. As with Hsiao (2012), this study classifies performance expectations highlighting the beneficial influence of online courses on learning performance as well as social expectations from classmates, co-workers, or teachers. In this context, the fourth level of the decision tree identified the performance expectations of adult learners from online courses and the social influence of the online community.

Conclusion

As a result, satisfaction, which is widely acknowledged in the literature, accurately predicts first-level intention to use. Utilitarian value and perceived usability are the two characteristics that determine satisfaction. It is critical to explain the use intentions of adult learners by pointing out that these two variables are based on the findings of studies that provide significant outcomes rather than on models found in the literature. However, it should be noted that Ryan and Deci (2000) emphasized the utilitarian value variable and that the perceived usability variable was generated using the TAM model. When the model's variables are analysed, it is discovered that the information quality and service quality variables originate from the Updated IS Model. Bandura's (1999) social cognition theory incorporates the variable of output expectancies. In summary, the TAM, ECM, Updated IS, model, self-determination theory (SDT), and social cognitive theory (SCT), all of which are commonly stressed in the literature, appear to be significant predictors of adult learners' usage intentions.

Limitations and further research

This research should be interpreted in light of its limitations. The first limitation caused from sample. Data was collected from only the Turkish sample. Researchers should be cautious about generalizing results from a single culture-based sample. The second limitation originates from the data analysis method. Unlike other methods of analysis, machine learning performed using WEKA allows for better flexibility. This flexibility gives us the opportunity to determine the minimum number of participants for each node. In this research, the minnumobj value was set to 2. This value has a direct effect on the decision tree. Repeating the analysis with WEKA with a different minnumobj value, results in a different decision tree. While this condition is regarded as providing for considerable flexibility in presenting the possible solutions to a research problem under various circumstances, it may also result in divergent interpretations. As such, it should be noted as a research limitation. It is encouraged to conduct further research with larger samples and also compare the results of the analyses of structural equation modelling and machine learning.

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