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The role of individual differences on epistemic curiosity (EC) and self-regulated learning (SRL) during e-learning: the Turkish context

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Abstract: This study aims to examine the relations and associations between gender, epistemic curiosity (EC), self-regulated learning (SRL), and attitudes toward e-learning in higher education students. The participants were 2438 (862 males, 1576 females) undergraduate students enrolled in a Turkish university. The regression analysis findings showed that although the effect size was low, attitudes towards e-learning can be predicted significantly by gender, EC, and SRL. Datasets are further analyzed using data mining. The findings of the association rule mining revealed that gender plays an influential role. Several association rules among EC, SRL, and attitudes towards e-learning were detected for female students. The results provide recommendations about using data mining as a statistical method in educational and psychological research.

1. INTRODUCTION

With the increasing prevalence of Internet-based courses, attention has been placed on e-learning in educational institutions due to its numerous benefits including the absence of physical and temporal limits, the ease of accessing the material, and the cost-effectiveness (Altun et al., 2021; Howland & Moore, 2002). Specifically, the constructivist approach has had an impact on e-learning which resulted in the design of "constructivist e-learning environments" (CEEs) such as WebQuests, online courses, courses with simulations via computer management games and simulations (Martens et al., 2007, p.82). More specifically, the CEEs are based on constructivist principles which aim to provide challenging, authentic, and meaningful context. In this way, the learners can become intrinsically motivated during their learning process (Bastiaens & Martens, 2000).

As for the field of education, the e-learning environments accompanied by the widespread use and availability of computers and smartphones led to a shift in the process of teaching and learning (Erarslan & Topkaya, 2017). E-learning has started to offer platforms that are learner-centered, convenient for the learners' own pace of learning, motivating, and available in various

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forms of sources to practice and interact with others through web-based tools (Mohammadi et al., 2011). Recent research indicated that the adoption of e-learning has been widely affected by student-related factors (Bhuasiri et al., 2012). Student attitudes toward e-learning have been crucial in various learning environments. As highlighted by Maio et al. (2018), strong attitudes can guide behavior and positive attitudes toward learning which contributes to the effective use of learning strategies. Therefore, possessing positive attitudes and behaviors regarding e-learning has been considered crucial for the acceptance, easiness, usability, and adoption of online learning (Aixia & Wang, 2011; Martins & Kellermanns, 2004; Selim, 2007).

The current COVID-19 pandemic led to a sudden shift to e-learning in higher education. This sudden transition to e-learning took place beyond the preferences of the students. To put it another way, with the emergency action plan put into effect by the universities, not only the students who deliberately and willingly preferred distance education, but all students had to take all their courses remotely. Under these conditions, it became more important to find out which variables affect students' development of positive or negative attitudes towards e-learning. As Gunnarsson (2001) and Suanpang (2007) revealed in their studies, there is a significant relationship between the students' attitudes and their learning achievement in an online course.

1.1. Gender and Attitudes Towards E-Learning

Gender is considered among the influential factors in students' attitudes toward e-learning. Attitudes toward learning in technology-enhanced environments, such as e-learning, are closely related to how much people are engaged with technology. According to Colley and Comber (2003), males approach computers like toys. They tend to figure out how it works and try to master using them. On the other hand, females regard computers as tools rather than a puzzle to solve. Consistent with these views, several studies showed that men are more interested and more engaged in technology than women, as a result, they are more experienced in using computers (Chen, 1986; Gnambs, 2021; Heo & Toomey, 2020; Temple & Lips, 1989). Due to this prior experience, males were more positive toward computers and computer-related tasks and jobs (Whitley, 1997), which may lead to more positive attitudes toward e-learning as found in several studies (Liaw & Huang, 2011; Ong & Lai, 2006; Wang et al., 2009).

1.2. Self-Regulated Learning and Attitudes Towards E-Learning

Effective learning requires students to self-regulate their motivation, cognition, and behavior (Zimmerman, 1989). Self-regulated learning (SLR) is defined as "the degree to which students are metacognitively, motivationally, and behaviorally active participants in their learning process" (Zimmerman, 2008, p.2). In other words, self-regulated learning involves high motivation and self-direction. According to Zimmerman (2000), self-regulated learning (SRL) comprises three cycles (1) forethought, (2) performance or volitional control, and (3) self-reflection. The forethought phase includes two components namely, task analysis and motivational beliefs. In this stage, students are expected to create an effective learning plan by identifying their learning goals. These goals should be challenging but attainable, proximal, and hierarchically organized with larger overarching goals. Apart from setting goals, students should allocate the appropriate amount of time to complete the learning tasks which should be framed and reframed by the educators to serve basis for future planning. As for the performance phase, self-control and self-observation components are emphasized for students which are expected to use different strategies towards achieving their learning goals as well as to observe the effectiveness of these to complete their learning tasks. Educators can help students at this phase by teaching and modeling various strategies that can be used for completing a learning task. In this stage, educators should equip students with a variety of strategies they can use for completing a task. Finally, the self-reflection phase includes self-judgment and self-reaction which requires students to self-reflect on their learning outcomes and experiences. This phrase highlights the importance of focusing on what students can learn from their experiences and improve it next time. Simply, self-regulation addresses the self-generated thoughts, feelings, and actions of students which helps them attain the pre-defined goals (Zimmerman, 1994) and aids with the achievement of students in their learning (McCoach, 2002).

Recent research on SRL revealed that many factors are closely related to students' self-regulated learning. To illustrate, in a study conducted by Cazan (2012), self-regulation was found to have a positive relationship with academic adjustment. Similarly, Zimmerman and Kitsantas (2014) emphasized the predictive role of self-regulation in students' grade point average (GPA) and their academic performance. All learning environments, online or not, require learners to attend class, learn the material, submit homework, and do group work (Paul & Jefferson, 2019). However, e-learning environments, unlike face-to-face learning environments, are learner-centered and require autonomy as they present many choices for the learners (Andrade & Bunker, 2011). In addition, e-learning requires them to be digitally skillful to be able to find their way around the learning interface (Hillman et al., 1994). Thus, in e-learning, the control of the process is mostly with the learner and requires the learner to manage his learning and to choose among different options to manage the process. Therefore, success in e-learning is closely related to the self-regulated learning levels experienced by learners (Nikolaki et al., 2017).

1.3. Curiosity and E-learning Attitudes

Apart from the importance of e-learning, the interest in curiosity has gained attention and highlighted the scientific interest in multiple disciplines (Dan et al., 2020). Different disciplinary approaches have proposed various models and reported different to measure curiosity. Initially, epistemic curiosity (EC) is defined as the motive to seek, obtain and make use of new knowledge (Berlyne, 1954; Litman, 2005; Loewenstein, 1994). To put it simply, it is a multifaceted construct consisting of distinctive yet highly correlated dimensions (Nakamura et al., 2021). Berlyne (1966) emphasized two dimensions of EC: diversive and specific. While diversive EC is motivated by feelings of boredom and desire to seek stimulation regardless of source or content and specific EC is motivated by curiosity and initiated a detailed investigation of novel stimuli to acquire new information (p.31). These two dimensions were found to be highly correlated by Litman and Spielberger (2003) who introduced another dimension, the feeling of deprivation. Additionally, Litman (2005) added two more dimensions to EC labeled as Interest-type (I-type) and Deprivation-type (D-type). First, I-type EC is defined as "a desire for new information anticipated to increase pleasurable feelings of situational interest" whereas D-type EC is based on "a motive to reduce unpleasant experiences of feeling deprived of new knowledge" (Lauriola et al., 2015, p. 202). The two dimensions were investigated by distinguished scholars who explored their association with learning and school performance (Eren & Coskun, 2016), acquisition of knowledge (Rotgans & Schmidt, 2014), and self-regulated behavior (Lauriola et al., 2015). Finally, research on individual differences in EC suggests that its I-type and D-type dimensions are related to the variety of underlying processes, information-seeking activities as well as self-directed learning goals (Lauriola et al., 2015). Among the predictors of these differences is the use of different regulations strategies by the learner during the learning process.

Considering the current COVID-19 pandemic which led to a sudden shift to online learning, determining the impact of individual characteristics on students' attitudes towards e-learning is an important research area for educational researchers. Gender, EC, and SRL may be influential factors in students' attitudes toward e-learning. To this end, this study aims to find out the relations and associations among higher education students' gender, SRL, EC, and attitudes towards e-learning.

2. METHOD

2.1. Setting and Participants

The data of the study were collected in the 2020-2021 Fall semester. The sample comprised 2348 (862 males, 1576 females) undergraduate students enrolled in a foundation (non-profit, private) university in Turkey. The participants were studying in various disciplines such as Foreign Languages (N=506), Social Sciences (N=362), Medical Sciences (265), Communication (N=184), Architecture (N=175), Law (N=144), and Other (802) (see Table 1).

Due to the COVID 19 pandemic, all students were taking all their courses online. For this study, they volunteered and filled in the online questionnaires. It was stated to all participants that the questionnaires were anonymous and that they could withdraw at any time. Informed consent was received with yes / no screen questions from all participants before filling out the online questionnaires.

Table 1. *Summary of participants' gender, department, and EL, SL, E-Learn Scales Quarters*[*].

Sex	f	%	Department	f	%	Quarter	Scale		
							EC (f)	SL (f)	E-Learn (f)
Man	862	35%	Foreign Languages	506	21%	First	390	478	489
Woman	1576	65%	Social Sciences	362	15%	Second	834	719	796
			Medical Sciences	265	11%	Third	778	792	691
			Communication	184	8%	Forth	436	449	462
			Architecture	175	7%				
			Law	144	6%				
			(Other)	802	32%				
TOTAL	2438	100%		2438	100%		2438	2438	2438

*Rounded to the nearest decimal.

2.2. Data Collection Tools

2.2.1. The curiosity and exploration inventory-ii

For this study, the Turkish version (Acun et al., 2013) of The Curiosity and Exploration Inventory-II (Acun et al., 2013) developed by Kashdan (2009) was used to measure the epistemic curiosity levels of the students. The self-report scale consists of 10 items with two subscales. The two subscales are the stretching subscale, which is the motivation for seeking information and new experience, and the acceptance of uncertainty and embracing subscale, which reflects the desire to discover the new, uncertain, and unpredictable in daily life. Students responded on a four-point frequency scale where 1=never and 4= always. Higher scores indicate higher epistemic curiosity. The validity and reliability of the original English version of the scale were tested with three different samples and alpha reliability coefficients were reported between .75 and .86 for these samples. The validity and reliability of the Turkish version were tested with two different samples and alpha reliability coefficients for these two samples were calculated as .81 and .82 (Acun et al., 2013). For the current study, the alpha reliability coefficient was calculated as .80.

2.2.2. Self-regulation scale

To measure the self-regulation of the students, the Turkish version (Duru et al., 2009) of the Self-Regulation Scale developed by Tuckman (2002) was used. The scale consists of 9 items –e.g. "I seem to have enough time to complete my work" and "I organize my time". Students responded on a four-point frequency scale where 1=never and 4= always. Higher scores indicate higher levels of self-regulation. The Alpha reliability coefficient for the original version was

.88 and for the Turkish version was.73. For the current study, the alpha reliability coefficient was calculated as.73.

2.2.3. Attitudes toward the e-learning scale

To measure students' attitudes towards online learning, the Attitude Scale Towards E-Learning Scale developed by Haznedar and Baran (2012) was used. The scale is a five-point Likert scale where 1= definitely disagree and 5= definitely agree. The scale consists of 20 items, e.g. “I like working at my own pace with e-learning” and “E-learning increases the productivity of the learner”. Higher scores indicate a positive attitude towards e-learning. The Alpha reliability coefficient of the scale was calculated as.93. For the current study, the alpha reliability coefficient was .97.

2.3. Data Analysis

The data in this study were analyzed in two steps. In the first step, multiple regression analysis was carried out to examine whether gender, EC, and SRL predict attitudes towards e-learning. Before the analysis, the suitability of the dataset for the analysis was tested. There was linearity as assessed by partial regression plots and a plot of studentized residuals against the predicted values. There was the independence of residuals, as assessed by a Durbin-Watson statistic of.086. Homoscedasticity was assessed by visual inspection of a plot of studentized residuals versus unstandardized predicted values and confirmed. For multicollinearity, tolerance values were assessed. All the values were greater than 0.1. No evidence of multicollinearity was detected. There were no studentized deleted residuals greater than ±3 standard deviations, no leverage values greater than 0.2, and values for Cook's distance above 1. Investigation of the Q-Q Plot confirmed the normality of the data.

In the second step, to further understand the relationships among the variables, the association rule mining was run. With the change in the type and amount of data, it was understood that it would not be possible to obtain meaningful information in the analysis of the available data with existing methods and technologies (Ayık et al., 2007). This limitation prompted researchers to study in-depth for new analysis methods. As a result of these studies, a new data analysis method, data mining has emerged, which enables the analysis of data from different angles and to summarize this data by converting it into useful information (Delavari et al., 2008; Narli et al., 2014). The researchers defined the data analysis method as the process of discovering meaningful information from data stacks using methodologies such as artificial intelligence, statistics, and machine learning (Tan et al., 2006; Aran et al., 2019). The purpose of data mining is to reveal the whole systematic relationships between variables that do not appear to be relational or are assumed to be unrelated (Luan, 2002). Data mining includes different analysis models within itself. Many studies have categorized these models in different classifications (Ayık et al., 2007; Baker & Yacef, 2009; Baradwaj & Pal, 2012; Delavari et al., 2008; Luan, 2002; Narli et al., 2014). The most general definition of the association rule is categorized in the descriptive model which tries to reveal which events can occur simultaneously by examining the relations of the variables in the dataset with each other. The analysis methods used in this study are described below.

2.3.1. Association rules mining

The association rule is aimed at examining the $X \rightarrow Y$ events in the form of cause and effect with each other. Analysis of association rule is performed with sequential or parallel and scattered algorithms depending on the characteristics of the data set. Algorithms such as Apriori, STEM, and AIS are called sequential algorithms and are preferred in cases in which the analyzed data set can be counted (Garcia et al., 2010). Methods such as count distribution, parallel data mining, and common candidate partitioned database are parallel and distributed algorithms and are used for the analysis of large data sets (Agrawal & Srikant, 1994; Inokuchi, et al., 2000; Zaki et al., 1997). In case the data set has a categorical structure, the apriori algorithm, which is one of the sequential algorithms, is often preferred in the analysis for the association rule (Agrawal & Srikant, 1994). In the scope of this study, the apriori algorithm was used for the association rule.

The Apriori Algorithm developed by Agrawal and Srikant (1994) is an algorithm that is generally used to determine product sales strategy, banking services, and social trends. Findings obtained with this algorithm are presented with support, confidence, lift, and coverage values (Zaki et al., 1997). The support value is the percentage equivalent of the data set of the rule obtained in the whole data set and is calculated with the following formula (Garcia et al., 2010; Merceron et al., 2010; Özçalıcı, 2017).

$$Support = \frac{n(X \cup Y)}{N}$$

In this formula $n(X \cup Y)$ refers to all cases in which X and Y are present together and N refers to the number of all cases in the total data set. In other words, this value shows the ratio of events or clusters in which X takes place to all events or sets for X and Y, which are different from each other (Güngör et al., 2013). The percentage equivalent of how much of the cases in which the X of the examined situation includes Y is the confidence value and is calculated with the following formula.

$$Confidence = \frac{n(X \cup Y)}{n(X)}$$

In this formula, $n(X \cup Y)$ corresponds to the number of cases in which both X and Y, while $n(X)$ only corresponds to the number of cases in which X is presented. The confidence value can only be zero if and only if there is no case in $n(X \cup Y)$ value, that is, X and Y together. Another important value obtained with the apriori algorithm is the lift value. The lift value, which expresses the rate of statistical realization of X and Y independently of each other, is calculated with the following formula.

$$Lift\ (X \rightarrow Y) = \frac{Confidence\ (X \rightarrow Y)}{Support\ (Y)}$$

Lift value, which can take a value between 0 and ∞ according to this formula, is a parameter that helps to interpret how often events occur (Brin et al., 1997). Another important parameter for the apriori algorithm is the coverage value. Coverage values are parameters that show how often the present rule can be applied and it is calculated by the following formula (Garcia et al, 2010; Merceron et al., 2010).

$$Cover = Support(X) = P(X)$$

According to this formula, the coverage value of a situation is equal to the ratio of the cases in which X is located. Therefore, it takes a value between 0 and 1.

For association rules mining, all the variables should be categorical. In this study all the variables, except gender, were continuous. Therefore, EC, SRL, and attitudes towards e-learning variables were divided into 4 groups. For grouping, the students into curiosity, self-regulation, and attitudes towards e-learning groupings, the visual binning procedure was employed using SPSS. Binning was performed by applying cut-points at the mean and ±1 standard deviation. For each variable, four binned categories were established. (Q1 = low , Q2 = moderately low, Q3 = moderately high, Q4 = high).

For regression we used IBM SPSS 25 and the association rules analyses were carried out using R Studio 1.3.1093 with R version 4.0.3 rules package. For the visualization of findings, we used diagrams.net 14.1.8.

3. RESULT

As previously stated, in the present study we proposed a possible relationship between gender, EC and SRL, and attitudes towards e-learning. The following section examines and reports the obtained results in detail.

3.1. Regression Analysis

To predict attitudes towards online learning from gender, EC, and SRL, a multiple regression analysis was run (see Table 2). Based on the results of regression analysis gender, EC and SRL statistically significantly predicted attitudes towards online learning, $F(3, 2447) = 44.570$, $p < .001$. All four variables added statistically significantly to the prediction, $p < .05$. R^2 for the overall model was 5% with an adjusted R^2 of 5%. However, the effect size was small according to Cohen (1988).

Table 2. *Multiple regression results for* attitudes *towards online learning.*

Online Learning Attitude	B	95% CI for B Lower Bound	95% CI for B Upper Bound	SE B	β	R^2	ΔR^2
Constant	15.292	8.31	22.27	3.559		.05	.05
Gender	2.005	.172	3.84	.935	.043*		
Curiosity	.348	.816	1.23	.090	.079**		
Self-Regulation	1.022	.172	3.84	.105	.198**		

Note: *B*= unstandardized regression coefficent; CI= confidence interval; SE B= standard error of the coefficient; β = standardized coefficient; R^2 = coefficient of determination; ΔR^2 = adjusted R^2.
**p*< .05. ***p*<.01

3.2. Association Rules Mining

To gain an in-depth analysis of the obtained data, data mining was further employed. We used the association rule mining technique. Association rule mining is generally defined as the process of exploring meaningful knowledge within data sets by making use of such methodology as artificial intelligence, statistics, and machine learning (Tan et al., 2006). To put it simply, association rule data mining (descriptive category) was applied by searching data for frequent if-then patterns and identifying the most important relationships. The following section of this study summarizes the results.

While establishing the association rule, the minimum support value was determined as 0.01 and the confidence value as 0.8. A total of 29 rules were reached that provide these values. The summary information on rule length distribution, support, confidence, coverage, lift, and frequency values regarding all rules were given in Table 3.

Table 3. *Summary of quality measures of association rules**.

	Rule length distribution (lhs + rhs)	Support (%)	Confidence (%)	Coverage (%)	Lift	Count (f)
Minimum	3	0.01	0.8	0.01	1.23	26
1st Quarter	3	0.01	0.82	0.01	1.26	29
Median	3	0.01	0.86	0.02	1.33	35
Mean	3.20	0.02	0.87	0.02	1.35	40
3rd Quarter	3	0.02	0.91	0.02	1.4	47
Maximum	4	0.04	1	0.04	1.54	86

*Rounded to the nearest decimal.

When the distribution of the found rules was examined, it was seen that the minimum rule length (lhs + rhs) was 3 (n = 33) and the maximum rule length was 4 (n = 18). The minimum support and coverage value obtained was 0.01, and the highest was 0.04. It was found that the highest Conf value was obtained as 100%. The least repeating rule was n=26, while the most repeating rule was repeated n=86 times. Lastly, the average lift value was found to be 1.36 (min: 1.23, max: 1.50).

The 29 rules within the scope of this research will be presented in two categories. 22 of the rules were composed of different rule sets, including department variables of students, and the remaining 7 rules were composed of only quarters in measurement tools.

3.2.1. Department based findings

A total of 3 rules were found for students who enrolled in EduIns. (n=80, 3,3%), (see Table 3) When these rules were examined, it was revealed that students with 3rdQ (supp: 0.02; conf: 0.95; cov: 0.02; lift; 1.47; f: 39) on the E-Learn scale, 2ndQ (supp: 0.01; conf: 1; cov: 0.01; lift; 1.54; f: 26) on the SRL scale, and 3rdQ (supp: 0.01; conf: 0.87; cov: 0.01; lift; 1.34; f: 27) on the EC scale were female (see Table 4).

Table 4. *Association rules and their support, confidence, coverage, and lift values**.

Rule	Mathematical Rule lhs → rhs	Support (%)	Confidence (%)	Coverage (%)	Lift	Count (f)
[R1]	(Dep=EduIns) ∪ (E-Learn=3rdQ) → (Sex=F)	0.02	0.95	0.02	1.47	39
[R2]	(Dep=EduIns) ∪ (SRL=2ndQ) →(Sex=F)	0.01	100	0.01	1.54	26
[R3]	(Dep=EduIns) ∪ (EC=3rdQ) →(Sex=F)	0.01	0.87	0.01	1.34	27

*F: Female, Dep: Department, Q: Quarter

In EduFa (n=122, 5%), it was understood that female participants were in the 2nd and 3rd quarters [R4…R9] in all E-Learn, SRL, and EC scales (see Table 5). In other words, in one or more of these scales, no pattern was found for education faculty students who were in the 1st and 4th quarters.

Table 5. *Association rules and their support, confidence, coverage, and lift values**.

Rule	Mathematical Rule lhs → rhs	Support (%)	Confidence (%)	Coverage (%)	Lift	Count (f)
[R4]	(Dep=EduFa) ∪ (E-Learn=3rdQ) →(Sex=F)	0.01	0.92	0.02	1.42	35
[R5]	(Dep=EduFa) ∪ (SRL=2ndQ) →(Sex=F)	0.01	0.82	0.02	1.26	36
[R6]	(Dep=EduFa) ∪ (EC=3rdQ) →(Sex=F)	0.01	0.83	0.01	1.28	29
[R7]	(Dep=EduFa) ∪ (SRL=3rdQ) →(Sex=F)	0.01	0.88	0.02	1.35	35
[R8]	(Dep=EduFa) ∪ (E-Learn=2ndQ) →(Sex=F)	0.01	0.85	0.02	1.31	34
[R9]	(Dep=EduFa) ∪ (EC=2ndQ) →(Sex=WF	0.02	0.90	0.02	1.38	43

*F: Female, Dep: Department, Q: Quarter

A total of 7 rules for MedVoc (n=144, 5.9%) and MedSci (n=265, 10.8%) were obtained (see Table 5). MedVoc students, those in the 2nd [R10] and 4th [R11] quarters in SRL, and those in the 2nd [R12] quarter in EC were identified as female.

Table 6. *Association rules and their support, confidence, coverage, and lift values**.

Rule	Mathematical Rule lhs → rhs	Support (%)	Confidence (%)	Coverage (%)	Lift	Count (f)
[R10]	(Dep=MedVoc) ∪ (SRL=2thQ) →(Sex=F)	0.01	0.82	0.01	1.26	27
[R11]	(Dep=MedVoc) ∪ (SRL=4ndQ) →(Sex=F)	0.01	0.90	0.01	1.39	27
[R12]	(Dep=MedVoc) ∪ (EC=2ndQ) →(Sex=F)	0.02	0.86	0.02	1.33	50
[R13]	(Dep=MedSci) ∪ (SRL=3rdQ) ∪ (E-Learn=1stQ) →(Sex=F)	0.01	0.91	0.01	1.4	30
[R14]	(Dep=MedSci) ∪ (EC=2ndQ) ∪ (SRL=2ndQ) →(Sex=F)	0.01	100	0.01	1.54	29
[R15]	(Dep=MedSci) ∪ (EC=2ndQ) ∪ (SRL=3rdQ) →(Sex=F)	0.01	0.97	0.01	1.5	32
[R16]	(Dep=MedSci) ∪ (EC=2ndQ) ∪ (E-Learn=2ndQ) →(Sex=F)	0.01	0.95	0.02	1.46	36

*F: Female, Dep: Department, Q: Quarter

Furthermore, as shown in the Table 6 above, For MedSci students, those in SRL 3rdQ and E-Learn 1stQ (supp: 0.01; conf: 0.91; cov: 0.01; lift; 1.4; f: 30) were determined to be women, and along with that, both EC 2nd and; [R14] those in SRL 2nd (*supp:* 0.01; *conf:* 1; *cov:* 0.01; *lift;* 1.54; *f:* 29) quarter, [R15] those in SL 3rd (*supp:* 0.01; *conf:* 0.97; *cov:* 0.01; *lift;* 1.5; *f:* 32) quarter or, [R16] those in E-Learn 2nd (*supp:* 0.01; *conf:* 0.95; *cov:* 0.02; *lift;* 1.46; *f:* 36) quarter were obtained as the pattern of female students.

The last section of the department-based rules consists of 6 rules involving Arch students. The findings revealed that the participants from Arch in E-Learn 1st [R18] and 3rd [R19] quarter, in 1st [R17] and 2nd [R22] quarters in EC and SRL 2nd [R20] and 3rd [R21] were female students (see Table 7).

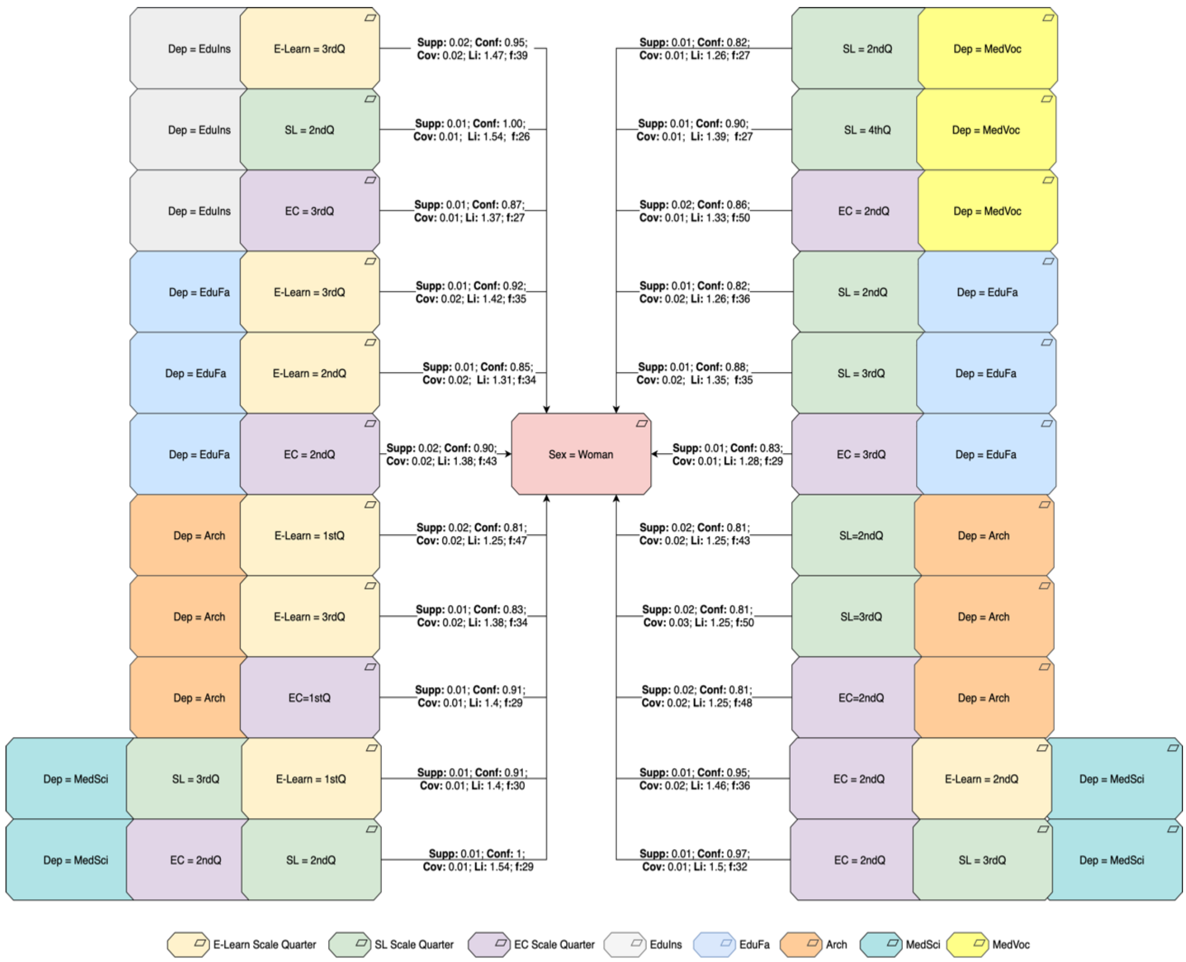
Table 7. *Association rules and their support, confidence, coverage, and lift values*.*

Rule	Mathematical Rule lhs → rhs	Support (%)	Confidence (%)	Coverage (%)	Lift	Count (f)
[R17]	(Dep=Arch) ∪ (EC=1stQ) →(Sex=F)	0.01	0.91	0.01	1.4	29
[R18]	(Dep=Arch) ∪ (E-Learn=1stQ) →(Sex=F)	0.02	0.81	0.02	1.25	47
[R19]	(Dep=Arch) ∪ (E-Learn=3rdQ) →(Sex=F)	0.01	0.83	0.02	1.28	34
[R20]	(Dep=Arch) ∪ (SRL=2ndQ) →(Sex=F)	0.02	0.81	0.02	1.25	43
[R21]	(Dep=Arch) ∪ (SRL=3rdQ) →(Sex=F)	0.02	0.81	0.03	1.25	50
[R22]	(Dep=Arch) ∪ (EC=2ndQ) →(Sex=F)	0.02	0.81	0.02	1.25	48

*F: Female, Dep: Department, Q: Quarter

Finally, based on the gathered data all department-based rules were given in Figure 1. When all these rules were examined, it was understood that there was a pattern in the data of EduIns, EduFa, MedVoc, MedSci, and Arch departments in this data set, which includes participants from 17 different departments. Therewithal, no pattern was obtained for male participants even though there were both female and male participants. The most unusual finding regarding the department-based rules was that the predictor variable of all rules points to female participants. In other words, the main element of the pattern created in all rules was the gender variable of the female participants.

Figure 1. *Departmental rules.*



3.2.2. Scales based findings

All rules based on scales were given in the Table 8. When all these rules were examined, it was concluded that those with EC 1stQ and also those in [R23] SL 4th quarter (supp: 0.02; conf: 0,93; cov: 0.02; lift; 1.44; f: 54), [R24] E-learn 3rdQ (supp: 0.03; conf: 0.80; cov: 0.04; lift; 1.23; f: 76), [R24] SRL 3rdQ (supp: 0.04; conf: 0.84; cov: 0.04; lift; 1.3; f: 86) were female.

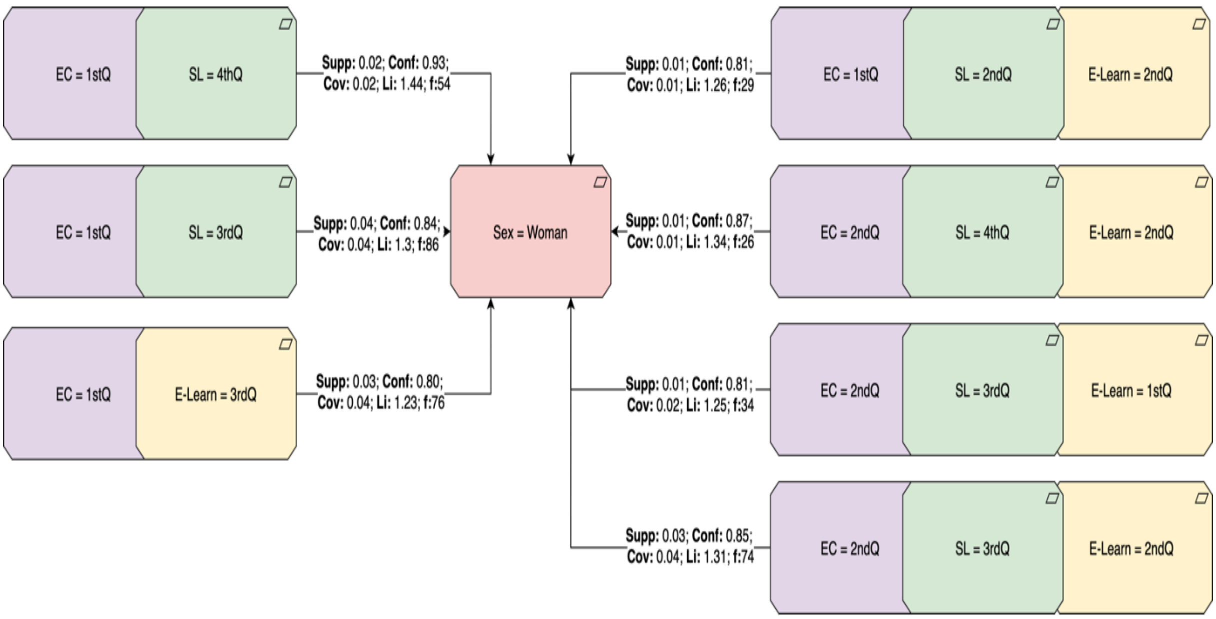
Table 8. *Association rules and their support, confidence, coverage, and lift values*.*

Rule	Mathematical Rule lhs → rhs	Support (%)	Confidence (%)	Coverage (%)	Lift	Count (f)
[R23]	(EC=1stQ) ∪ (SRL=4thQ) →(Sex=F)	0.02	0.93	0.02	1.44	54
[R24]	(EC=1stQ) ∪ (E-Learn=3rdQ) →(Sex=F)	0.03	0.80	0.04	1.23	76
[R25]	(EC=1stQ) ∪ (SRL=3rdQ) →(Sex=F)	0.04	0.84	0.04	1.3	86
[R26]	(EC=1stQ) ∪ (SRL=2ndQ) ∪ (E-Learn=2ndQ) →(Sex=F)	0.01	0.81	0.01	1.26	29
[R27]	(EC=2ndQ) ∪ (SRL=4thQ) ∪ (E-Learn=2ndQ) →(Sex=F)	0.01	0.87	0.01	1.34	26
[R28]	(EC=2ndQ) ∪ (SRL=3rdQ) ∪ (E-Learn=1stQ) →(Sex=F)	0.01	0.81	0.02	1.25	34
[R29]	(EC=2ndQ) ∪ (SRL=3rdQ) ∪ (E-Learn=2ndQ) →(Sex=F)	0.03	0.85	0.04	1.31	74

*F: Female, Dep: Department, Q: Quarter

The remaining 4 rules on scale-based were 4 rule lengths. Accordingly, all participants who fulfilled the requirements [R26] (EC=1stQ) ∪ (SRL=2ndQ) ∪ (E-Learn=2ndQ) and [R27] (EC=2ndQ) ∪ (SRL=4thQ) ∪ (E-Learn=2ndQ) were women. Finally, along with EC 2ndQ and SRL 3rdQ, all participants in E-Learn, both from 1stQ and 2ndQ were also stated as women. All scale-based rules were given in Figure 2 below.

Figure 2. *Scale based rules.*



4. DISCUSSION and CONCLUSION

As previously stated, in the present study we proposed that individual differences might be an active and influential on higher education students' attitudes toward e-learning. The statistical analysis of multiple regression revealed that gender, EC and SRL were significant predictors of attitudes towards e-learning. However, the effect size was low. So, to further analyze the relations among the variables, we conducted association rule mining. As expected, we could detect several associations among variables that cannot be detected via regression models. According to the association rule in the descriptive model category, gender was found to have a predictive role in the two behaviors. Specifically, females outperformed males both in SRL and EC during online learning. These findings were contrary to previous studies that revealed no significant gender differences with respect to SRL (Çalışkan & Sezgin-Selcuk, 2010; Hargittai & Shafer, 2006; Yükseltürk & Bulut, 2009). Besides, the findings were opposite to the study conducted by Bashir and Bashir (2016) indicating that males showed higher self-regulation as compared to females. The only partial similarity was reported by Senler and Sungur-Vural (2012) stating that females showed higher self-regulation and effort regulation compared with males.

Considering the statistical analysis methods used in the study, it is important to evaluate the findings revealed by data mining. The association rule used in this study, although it is less used in educational sciences, has wide usage in several areas as Computer Science (Chen et al. 2021), Engineering (Çakır et al., 2021), Decision Sciences (Prathama et al.2021), Mathematics (Li et al., 2020) Business, Management and Accounting (Moodley et al., 2020), Medicine and Dentistry (Tandan et al., 2021), Social Sciences (Cömert & Akgün, 2021), Energy (Odabaşı & Yıldırım, 2019), Environmental Science (Nagata et al., 2014) and Psychology (Elia et al., 2019). Besides, in order to compare the performance of this analysis method, which includes more than one algorithm, many variables such as the distribution, features, and characteristics of the data set should be considered. Therefore, it can be said that which algorithm gives better performance from association rules varies according to the properties of the dataset (Borgelt & Kruse, 2002). With data mining techniques in which appropriate algorithms are selected, it seems possible to reveal detailed characteristic relationships about students and to make predictions for the future (Arora & Badal, 2014).

Based on these overviews, the present study revealed that gender might have a predictive role on SRL and EC among higher education students during e-learning which should be addressed in further studies. Similar to face-to-face education, individual differences have an active and influential role in teaching and learning online as well. Therefore, we propose that future research should examine the role of such personal characteristics in various educational contexts to provide suggestions for more effective pedagogical practices. To gather in-depth information, we also recommend that data mining can be used as a statistical method in educational and psychological research.

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Declaration of Conflicting Interests and Ethics

The authors declare no conflict of interest. This research study complies with research publishing ethics. The scientific and legal responsibility for manuscripts published in IJATE belongs to the authors. **Ethics Committee Number**: Bahcesehir University, 10.02.2021 - 2021/02/16.

Authorship Contribution Statement

Ergun Akgun: Investigation, Resources, Visualization, Software, Formal Analysis, and Writing-original draft. **Enisa Mede:** Methodology, Supervision, Validation, Formal Analysis, and Writing. **Seda Sarac:** Methodology, Supervision, Validation, Formal Analysis, and Writing.

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REFERENCES

Acun, N., Kapıkıran, Ş., & Kabasakal, Z. (2013). Merak ve keşfetme ölçeği II: Açımlayıcı ve doğrulayıcı faktör analizleri ve güvenirlik çalışması [Trait Curiosity and Exploration Inventory-II: Exploratory and Confirmatory Factor Analysis and Its Reliability] *Türk Psikoloji Yazıları*, *16*(31), 74-85.

Agrawal, R., & Srikant, R. (1994, September, 487-489). *Fast algorithms for mining association rules.* Proc. of the 20th VLDB Conference, San Francisco, USA.

Aixia, D., & Wang, D. (2011). Factors influencing learner attitudes toward e-learning and development of e-learning environment based on the integrated e-learning platform. *International Journal of e-Education, e-Business, e-Management and e-Learning*, *1*(3), 264-268.

Altun, T., Akyıldız, S., Gülay, A., & Özdemir, C. (2021). Investigating education faculty students' views about asynchronous distance education practices during Covid-19 ısolation period. *Psycho-Educational Research Reviews*, *10*(1), 34–45.

Andrade, M.S., & Bunker, E.L. (2011). The role of SRL and TELEs in distance education: Narrowing the gap. In *Fostering self-regulated learning through ICT* (pp. 105-121). IGI Global. https://doi.org/10.4018/978-1-61692-901-5.ch007

Aran, O., Bozkir, A., Gok, B., & Yagci, E. (2019). Analyzing the views of teachers and prospective teachers on information and communication technology via descriptive data mining. *International Journal of Assessment Tools in Education, 6*(2), 314-329. https://doi.org/10.21449/ijate.537877

Arora, R.K., & Badal, D. (2014). Mining association rules to improve academic performance. *International Journal of Computer Science and Mobile Computing, 3*(1), 428-433.

Ayık, Y.Z., Özdemir, A., & Yavuz, U. (2007). Lise türü ve lise mezuniyet başarisinin, kazanilan fakülte ile ilişkisinin veri madenciliği tekniği ile analizi [Analysis of the relationship of high school type and high school graduation success with the faculty entered by data mining technique] *Atatürk Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, *10*(2), 441-454.

Baker, R.S., & Yacef, K. (2009). The state of educational data mining in 2009: A review and future visions. *Journal of Educational Data Mining*, *1*(1), 3-17. https://doi.org/10.5281/zenodo.3554657

Baradwaj B.K., & Pal, S. (2012). Mining educational data to analyze students' performance. arXiv preprint arXiv:1201.3417. https://doi.org/10.48550/arXiv.1201.3417

Bashir, H., & Bashir, L. (2016). Investigating the relationship between self-regulation and spiritual intelligence of higher secondary school students. *Indian Journal of Health and Wellbeing*, *7*(3), 327.

Bastiaens, T.J., & Martens, R.L. (2000). Conditions for web-based learning with real events. In *Instructional and cognitive impacts of web-based education* (pp. 1-31). IGI Global. https://doi.org/10.4018/978-1-878289-59-9.ch001

Berlyne, D.E. (1966). Curiosity and exploration. *Science, 153*(3731), 25-33. https://doi.org/10.1126/science.153.3731.25

Berlyne, D.E. (1954). A theory of human curiosity. *British Journal of Psychology, 45,* 180–191.

Bhuasiri, W., Xaymoungkhoun, O., Zo, H., Rho, J.J., & Ciganek, A.P. (2012). Critical success factors for e-learning in developing countries: A comparative analysis between ICT experts and faculty. *Computers & Education*, *58*(2), 843-855. https://doi.org/10.1016/j.compedu.2011.10.010

Borgelt, C., & Kruse, R. (2002). Induction of association rules: Apriori implementation. In *Compstat* (pp. 395-400). Physica-Verlag Heidelberg.

Brin, S., Motwani, R., Ullman, J.D., & Tsur, S. (1997, June, 255-264). *Dynamic itemset counting and implication rules for market basket data.* Proceedings of the 1997 ACM SIGMOD international conference on Management of data, New York, USA. https://doi.org/10.1145/253260.253325

Cazan, A.M. (2012). Self-regulated learning strategies–predictors of academic adjustment. *Procedia-Social and Behavioral* Sciences, *33*, 104-108. https://doi.org/10.1016/j.sbspro.2012.01.092

Chen, M. (1986). Gender and computers: The beneficial effects of experience on attitudes. *Journal of Educational Computing Research*, *2*(3), 265-282. https://doi.org/10.2190%2FWDRY-9K0F-VCP6-JCCD

Chen, S., Yuan, Y., Luo, X.R., Jian, J., & Wang, Y. (2021). Discovering group-based transnational cyber fraud actives: A polymethodological view. *Computers & Security*, 102217. https://doi.org/10.1016/j.cose.2021.102217

Colley, A., & Comber, C. (2003). Age and gender differences in computer use and attitudes among secondary school students: what has changed?. *Educational Research*, *45*(2), 155-165. https://doi.org/10.1080/0013188032000103235

Cömert, Z., & Akgün, E. (2021). Game preferences of K-12 level students: analysis and prediction using the association rule. *Ilkogretim Online, 20*(1), 435-455. http://doi.org/10.17051/ilkonline.2021.01.039

Çakır, E., Fışkın, R., & Sevgili, C. (2021). Investigation of tugboat accidents severity: An application of association rule mining algorithms. *Reliability Engineering & System Safety, 209*, 107470. https://doi.org/10.1016/j.ress.2021.107470

Çalışkan, S., & Sezgin-Selçuk, G. (2010). Üniversite öğrencilerinin Fizik problemlerinde lullandıkları özdüzenleme stratejileri: Cinsiyet ve üniversite etkileri [Self-regulated strategies used by undergraduate students in physics problems: effects of gender and university]. *Dokuz Eylül Üniversitesi Buca Eğitim Fakültesi Dergisi*, 27(1), 50-62.

Dan, O., Leshkowitz, M., & Hassin, R.R. (2020). On clickbaits and evolution: Curiosity from urge and interest. *Current Opinion in Behavioral Sciences*, *35*, 150-156. https://doi.org/10.1016/j.cobeha.2020.09.009

Delavari, N., Phon-Amnuaisuk, S., & Beikzadeh, M.R. (2008). Data mining application in higher learning institutions. *Informatics in Education-International Journal*, *7*, 31-54.

Duru, E., Balkıs, M., Buluş, M., & Duru, S. (2009, October, 57-73). *Öğretmen adaylarında akademik erteleme eğiliminin yordanmasında öz düzenleme, akademik başarı ve demografik değişkenlerin rolü [The role of self-regulation, academic achievement and demographic variables in the prediction of academic procrastination in teacher candidates].* 18th Educational Sciences Congress, İzmir, Turkiye.

Elia, G., Solazzo, G., Lorenzo, G., & Passiante, G. (2019). Assessing learners’ satisfaction in collaborative online courses through a big data approach. *Computers in Human Behavior, 92,* 589-599. https://doi.org/10.1016/j.chb.2018.04.033

Erarslan, A., & Topkaya, E.Z. (2017). EFL students attitudes towards e-learning and effect of an online course on students success in English. *The Literacy Trek*, *3*(2), 80-101.

Eren, A., & Coskun, H. (2016). Students' level of boredom, boredom coping strategies, epistemic curiosity, and graded performance. *The Journal of Educational Research*, *109*(6), 574-588. https://doi.org/10.1080/00220671.2014.999364

Garcia, E., Romero, C., Ventura, S., Castro, C., & Calders, T. (2010). Association rule mining in learning management systems. In V. Kumar (Ed.). *Handbook of educational data mining.* (pp. 93-106). Taylor & Francis Group.

Gnambs, T. (2021). The development of gender differences in information and communication technology (ICT) literacy in middle adolescence. *Computers in Human Behavior*, *114*, 1-10. https://doi.org/10.1016/j.chb.2020.106533

Gunnarsson, C.L. (2001). Development and assessment of students: Attitudes and achievement in a business statistics course taught online. *Interactive Multimedia Electronic Journal of Computer-Enhanced Learning*, *3*(2).

Güngör, E., Yalçın, N., & Yurtay, N. (2013, Kasım, 122-127). *Apriori algoritması ile teknik seçmeli ders seçim analizi [Selection Behavior Analysis of Technical Elective Courses Using Apriori Algorithm].* Pro. UZEM 2013 Ulusal Uzaktan Eğitim ve Teknolojileri Sempozyumu, Konya, Turkiye.

Hargittai, E., & Shafer, S. (2006). Differences in actual and perceived online skills: The role of gender. *Social Science Quarterly*, *87*(2), 432-448. https://doi.org/10.1111/j.1540-6237.2006.00389.x

Haznedar, Ö., & Baran, B. (2012). Eğitim fakültesi öğrencileri için e-öğrenmeye yönelik genel bir tutum ölçeği geliştirme çalişmasi [Development of a general attitude scale towards e-learning for faculty of education students]. *Eğitim Teknolojisi Kuram ve Uygulama*, *2*(2), 42-59.

Heo, M., & Toomey, N. (2020). Learning with multimedia: The effects of gender, type of multimedia learning resources, and spatial ability. *Computers & Education*, *146*, 103747. https://doi.org/10.1016/j.compedu.2019.103747

Hillman, D.C., Willis, D.J., & Gunawardena, C.N. (1994). Learner-interface interaction in dis tance education: An extension of contemporary models and strategies for practitioners. *American Journal of Distance Education*, *8*(2), 30-42. https://doi.org/10.1080/08923649409526853

Howland, J.L., & Moore, J.L. (2002). Student perceptions as distance learners in Internet-based courses. *Distance Education*, *23*(2), 183-195. https://doi.org/10.1080/0158791022000009196

Inokuchi, A., Washio, T., & Motoda, H. (2000, September, 13-23). *An apriori-based algorithm for mining frequent substructures from graph data*. Proceedings of the 2000 European symposium on the principle of data mining and knowledge discovery (PKDD’00), Lyon, France.

Kashdan, T.B. (2009). *Curious? Discover the missing ingredient to a fulfilling life.* William Morrow.

Lauriola, M., Litman, J.A., Mussel, P., De Santis, R., Crowson, H.M., & Hoffman, R.R. (2015). Epistemic curiosity and self-regulation. *Personality and Individual Differences*, *83*, 202-207. https://doi.org/10.1016/j.paid.2015.04.017

Li, H., Wu, Y.J., & Chen, Y. (2020). Time is money: Dynamic-model-based time series data-mining for correlation analysis of commodity sales. *Journal of Computational and Applied Mathematics, 370,* 112659. https://doi.org/10.1016/j.cam.2019.112659

Liaw, S.S., & Huang, H.M. (2011, September, 28-32). *A study of investigating learners' attitudes toward e-learning.* 5th International Conference on Distance Learning and Education, Paris, Fransa.

Litman, J. (2005). Curiosity and the pleasures of learning: Wanting and liking new information. *Cognition & Emotion*, *19*(6), 793-814. https://doi.org/10.1080/02699930541000101

Litman, J.A., & Spielberger, C.D. (2003). Measuring epistemic curiosity and its diversive and specific components. *Journal of Personality Assessment*, *80*(1), 75-86. https://doi.org/10.1207/S15327752JPA8001_16

Loewenstein, G. (1994). The psychology of curiosity: A review and reinterpretation. *Psychological Bulletin, 116*(1), 75-98. https://psycnet.apa.org/doi/10.1037/0033-2909.116.1.75

Luan, J. (2002). Data mining and its applications in higher education. *New Directions For Institutional Research, 2002*(113), 17-36.

Maio, G.R., Haddock, G., & Verplanken, B. (2018). *The psychology of attitudes and attitude change* (3rd ed.). Sage.

Martens, R., Bastiaens, T., & Kirschner, P.A. (2007). New learning design in distance education: The impact on student perception and motivation. *Distance Education*, *28*(1), 81-93. https://doi.org/10.1080/01587910701305327

Martins, L.L., & Kellermanns, F.W. (2004). A model of business school students' acceptance of a web-based course management system. *Academy of Management Learning & Education*, *3*(1), 7-26. https://doi.org/10.5465/amle.2004.12436815

McCoach, D.B. (2002). A validation study of the school attitude assessment survey. *Measurement and Evaluation in Counseling and Development, 35*(2), 66. https://doi.org/10.1080/07481756.2002.12069050

Merceron, A., Yacef, K., Romero, C., Ventura, S., & Pechenizkiy, M. (2010). Measuring correlation of strong symmetric association rules in educational data. *Handbook of Educational Data Mining*, 245-256.

Mohammadi, N., Ghorbani, V., & Hamidi, F. (2011). Effects of e-learning on language learning. *Procedia Computer Science*, *3*, 464-468. https://doi.org/10.1016/j.procs.2010.12.078

Moodley, R., Chiclana, F., Caraffini, F., & Carter, J. (2020). A product-centric data mining algorithm for targeted promotions. *Journal of Retailing and Consumer Services, 54*, 101940. https://doi.org/10.1016/j.jretconser.2019.101940

Nagata, K., Washio, T., Kawahara, Y., & Unami, A. (2014). Toxicity prediction from toxicogenomic data based on class association rule mining. *Toxicology Reports, 1*, 1133-1142. https://doi.org/10.1016/j.toxrep.2014.10.014

Nakamura, S., Darasawang, P., & Reinders, H. (2021). The antecedents of boredom in L2 classroom learning. *System, 98*, 102469. https://doi.org/10.1016/j.system.2021.102469

Narli, S., Aksoy, E., & Ercire, Y.E. (2014). Investigation of prospective elementary mathematics teachers' learning styles and relationships between them using data mining. *International Journal of Educational Studies in Mathematics*, *1*(1), 37-57.

Nikolaki, E., Koutsouba, M., Lykesas, G., Venetsanou, F., & Savidou, D. (2017). The support and promotion of self-regulated learning in distance education. *European Journal of Open, Distance and E-learning, 20*(1), 1-11.

Odabaşı, Ç., & Yıldırım, R. (2019). Performance analysis of perovskite solar cells in 2013–2018 using machine-learning tools. *Nano Energy, 56,* 770-791. https://doi.org/10.1016/j.nanoen.2018.11.069

Ong, C.S., & Lai, J.Y. (2006). Gender differences in perceptions and relationships among dominants of e-learning acceptance. *Computers in Human Behavior, 22*(5), 816-829. https://doi.org/10.1016/j.chb.2004.03.006

Özçalıcı, M. (2017). Veri madenciliğinde birliktelik kuralları ve ikinci el otomobil piyasası üzerine bir uygulama [Association Rules in Data Mining and an Application in Second Hand Car Market]. *Ordu Üniversitesi Sosyal Bilimler Araştırma Dergisi, 7*(1), 45-58.

Paul, J., & Jefferson, F. (2019). A comparative analysis of student performance in an online vs. face-to-face environmental science course from 2009 to 2016. *Frontiers in Computer Science, 1*,1-9. https://doi.org/10.3389/fcomp.2019.00007

Prathama, F., Senjaya, W.F., Yahya, B.N., & Wu, J.Z. (2021). Personalized recommendation by matrix co-factorization with multiple implicit feedback on the pairwise comparison. *Computers & Industrial Engineering, 152*, 107033. https://doi.org/10.1016/j.cie.2020.107033

Rotgans, J.I., & Schmidt, H.G. (2014). Situational interest and learning: Thirst for knowledge. *Learning and Instruction*, *32*, 37-50. https://doi.org/10.1016/j.learninstruc.2014.01.002

Selim, H.M. (2007). Critical success factors for e-learning acceptance: Confirmatory factor models. *Computers & Education*, *49*(2), 396-413. https://doi.org/10.1016/j.compedu.2005.09.004

Senler, B., & Sungur-Vural, S. (2012, September, 551-556). *Pre-service science teachers' use of self-regulation strategies related to their academic performance and gender.* The European Conference on Educational Research (ECER), Cadiz, Spain. https://doi.org/10.1016/j.sbspro.2014.09.242

Suanpang, P. (2007). Students experience online learning in Thailand. In S. Hongladarom (Ed.), *Computing and philosophy in Asia*, (pp. 240-.252). Cambridge Scholar Publishing.

Tan, P.N., Steinbach, M., & Kumar, V. (2006). *Introduction to data mining*. Addison Wesley.

Tandan, M., Acharya, Y., Pokharel, S., & Timilsina, M. (2021). Discovering symptom patterns of COVID-19 patients using association rule mining. *Computers in Biology and Medicine*, 104249. https://doi.org/10.1016/j.compbiomed.2021.104249

Temple, L., & Lips, H.M. (1989). Gender differences and similarities in attitudes toward computers. *Computers in Human Behavior*, *5*(4), 215-226. https://doi.org/10.1016/0747-5632(89)90001-0

Tuckman, B. (2002, August). Academic procrastinators: Their rationalizations and web-course performance. the Annual Meeting of the American Psychological Association, Chicago, IL.

Wang, Y.S., Wu, M.C., & Wang, H.Y. (2009). Investigating the determinants and age and gender differences in the acceptance of mobile learning. *British Journal of Educational Technology, 40*(1), 92-118. https://doi.org/10.1111/j.1467-8535.2007.00809.x

Whitley Jr, B.E. (1997). Gender differences in computer-related attitudes and behavior: A meta-analysis. *Computers in Human Behavior, 13*(1), 1-22. https://doi.org/10.1016/S0747-5632(96)00026-X

Yükseltürk, E., & Bulut, S. (2009). Gender differences in self-regulated online learning environment. *Journal of Educational Technology & Society*, *12*(3), 12-22.

Zaki, M.J., Parthasarathy, S., Ogihara, M., & Li, W. (1997). Parallel algorithms for discovery of association rules. *Data Mining and Knowledge Discovery, 1*(4), 343-373.

Zimmerman, B. J. (1989). A social cognitive view of self-regulated academic learning. *Journal of Educational Psychology, 81*(3), 329–339. https://psycnet.apa.org/doi/10.1037/0022-0663.81.3.329

Zimmerman, B.J. (1994). *Dimensions of academic self-regulation: A framework for education. Regulation of learning and performance*. Lawrence Erlbaum.

Zimmerman, B.J. (2000). Attaining self-regulation: A social cognitive perspective. In *Handbook of self-regulation* (pp. 13-39). Academic Press.

Zimmerman, B.J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal*, *45*(1), 166-183. https://doi.org/10.3102%2F0002831207312909

Zimmerman, B., & Kitsantas, A. (2014). Comparing students' self-discipline and self-regulation measures and their prediction of academic achievement. *Contemporary Educational Psychology, 39*(2), 145-155. https://doi.org/10.1016/j.cedpsych.2014.03.004