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Applying The CHAID Algorithm to Analyze How Achievement is Influenced by University Students' Demographics, Study Habits, and Technology Familiarity

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ABSTRACT

The purpose of this study is to analyze three separate constructs (demographics, study habits, and technology familiarity) that can be used to identify university students' characteristics and the relationship between each of these constructs with student achievement. A survey method was used for the current study, and the participants included 2,949 university students from 11 faculties of a public university in Turkey. A survey was used to collect data, and the data were analyzed using the chi-squared automatic interaction detection (CHAID) algorithm. The results of the study revealed that female students are significantly more successful than male students. In addition, the more introverted students, whether male or female, have higher grade point averages (GPAs) than those students who are more extroverted. Furthermore, male students who use the Internet more than 22 hours per week and use the Internet for up to six different aims have the lowest GPAs among all students, while female students who use the Internet for up to 21 hours per week have the highest GPAs among all students. The implications of these findings are also discussed herein.

Keywords

Higher education, Achievement, Gender, Technology, Motivation, Decision tree

Introduction

Because developments in the field of information and communication technology (ICT) have led to a technology-based culture, educators are now educating a new generation of students. Accordingly, one of the important issues to be addressed when designing technology-oriented learning environments is learners' characteristics. With regard to this issue, the education profession faces two challenges. The first issue is that today's learners, who have grown up as digital natives and thus are being defined as the Net generation, are vastly different from the generations of learners that preceded current 21st-century learners (Oblinger & Oblinger, 2005; Prensky, 2001). The second issue is that children are experienced in a new form of play, that is, multiplayer computer and video games, and these experiences have shaped their preferences and capabilities regarding learning (Prensky, 2001). Therefore, to provide today's learners with a better education and a better learning context, educators should consider the characteristics of these new learners.

Gender, working habits, motivation, media use, and book reading, as shown in Table 1, may influence Net generation students' academic performance. Motivation has been found to be a significant predictor of achievement among students (Ayub 2010; Chan, Wong, & Lo, 2012). In addition, gender has been correlated with achievement (Sarier, 2010; Veenstra & Kuyper, 2004). However, the use of technology by students has controversial results as well (Turner & Corucher, 2013; Junco, 2012). The research studies conducted on study habits did not always reveal consistent results in that while some found significant correlations between study habits and achievement (Yu, 2011), others did not (Olatoye & Ogunkola, 2008). The majority of the studies in Table 1, which have small sample sizes, focused on the dualities between motivation and achievement, and the use of technology and achievement. However, the current study deals with gender, university level and achievement, study habits and achievement, and the use of technology and achievement in one single study.

Review of related literature

The literature review of this study is presented beneath three subheadings: gender, university level, and achievement; study habits and achievement; and use of technology and achievement.

Gender, university level, and achievement

Conger and Long (2010) examined disadvantages that male students experienced with respect to grade-point average, credits earned, and persistence in college, and found that male students have lower GPAs and fewer credits in their first semester of college largely because they came to college with lower high-school grades. Female students' better high-school grades explain some of the gender disparity in performance, but differences in college course-taking and majors also explain gender gaps in credits, grades, persistence, and graduation.

A study on persistence and success in an academic program at a community college revealed that students' GPAs, cumulative hours attempted, and cumulative hours completed were significant predictors of persistence and that young male students were a high-risk group (Stewart & Levin, 2001). Veenstra and Kuyper (2004) also revealed that gender was an important variable for academic achievement and female students were found to have higher levels of motivation. Finally, it was indicated that there was a significant difference between the genders in favor of female students regarding academic achievement in secondary education (Sarier, 2010). The literature did not indicate any finding about the effect of both university level and gender on achievement in one study.

Study habits and achievement

The study habits construct in the current study is twofold: working style (individual or studying in a group) and motivation (intrinsic or extrinsic). Olatoye and Ogunkola (2008) reveal that study habits make a significant contribution to the prediction of achievement in physics. In addition, students who demonstrate higher academic achievement use a variety of study skills compared to students of lower academic achievement (Ergene, 2011; Fazal, Hussain, Majoja & Masood, 2012; Fayombo, 2011; Yu, 2011).

Group learning can contribute to more in-depth learning (Hall, Ramsay, & Raven, 2004). However, some studies indicate that group study is not a significant variable in academic achievement (Yu, 2011). As cited in Yu (2011), Schuman, Walsh, Olson, and Etheridge (1985) examined group studying, cramming, note-taking, reviewing of past exams, and re-reading of material, and concluded that none of these variables had a direct effect on grades.

Motivation, "which is primarily concerned with activation and persistence of behavior, is also partly rooted in cognitive activities" (Bandura, 1977, p. 193). Motivation can influence how, when, and what we learn (Schunk, 1991). There are two types of motivation: intrinsic and extrinsic. The difference between intrinsic and extrinsic motivation is that the former is the doing of an activity because the activity is interesting and enjoyable rather than the instrumental value associated with the activity (Ryan & Deci, 2000). Eymur and Geban (2011) examined the relationship between motivation and academic achievement of pre-service chemistry teachers and found a significant relationship between achievement and two intrinsic motivation subscales (to know and to experience simulation). They also found a significant difference between women and men with respect to intrinsic motivation.

In another study, a positive predictive effect of intrinsic motivation on academic achievement was found for both Indian immigrants and Indian adolescents (Areepattamannil, Freeman, & Klinger, 2011). Ayub (2010) also found a relationship between intrinsic and extrinsic motivation and the academic performance of college students in India. With regard to gender, the findings reveal that women are more intrinsically motivated, whereas men are more extrinsically motivated. Chan et al. (2012) found that intrinsic motivation had predictive effects on academic achievement for secondary students. The findings of Lynch (2006) also suggest that intrinsic motivation, but not extrinsic motivation, is associated with academic course grades. Conversely, in another study (Liao, Ferdenzi, & Edlin, 2012), motivation was found to not directly affect the academic achievement of either international or domestic students. However, they did find that for international students, both extrinsic and intrinsic motivations indirectly affected academic achievement through the mediating influence of efficacy regarding self-regulated learning, although this was not the case for domestic students.

The studies above had small sample sizes and focused only on either motivation or group learning. The focus of the current study is to examine the effect of working habits (i.e., individual learning and group learning), motivation, and gender on achievement in one single study.

Table 1. The studies related to academic achievement

Authors	Year	Participants	Method	Variables	Data analysis
Areepattamannil, Freeman, & Klinger	2011	355 Indian immigrants and 363 Indian adolescents	Descriptive	Intrinsic motivation, extrinsic motivation, and academic achievement	Descriptive, discriminant analysis, hierarchical multiple regression
Chan, Wong, & Lo	2012	1,381 students	Descriptive	Intrinsic motivation, achievement goals, and learning strategies	Exploratory factor analysis, structural equation modeling
Eymur & Geban	2011	168 pre-service teachers	Descriptive	Gender, motivation, and achievement	Independent sample *t*-test, ANOVA, Pearson correlation
Turner & Croucher	2013	371 undergraduate students	Quantitative	Media-use habits, need for cognition, and grade-point average	Multiple regression analysis
Sarier	2010	PISA data	Descriptive	Socioeconomic and sociocultural effect and achievement	Descriptive
Liao, Ferdenzi, & Edlin	2012	310 students	Quantitative	Motivation, self-regulated learning efficacy and academic achievement	ANOVA, linear multivariate regression
Conger & Long	2010	Not exact number	Quantitative	In grade-point average, credits earned, and persistence in col-lege.	Regression and decomposition
Topcu & Uzundumlu	2012	150 students	Descriptive	student-oriented factors, physiological variables, physical environment), and the variables focused on the academic and the measurement techniques used by them.	Principal component analysis
Junco	2012	1839	Descriptive	Time spent on Facebook, frequency checking of Facebook, frequency of Facebook activities, time spent for preparing class	Hierarchical (blocked) linear regression analysis
Whitley	1997	82 studies	Meta-analysis	Gender difference, computer-related attitudes, behavior	Effect size, Q statistics, partial correlation
Hargittai & Hinnant	2010	270 adults	Descriptive	Users' education, autonomy of use, online experiences, and quality of equipment	Ordinary least squares regression

The use of technology and achievement

A new study that reviewed 154 qualifying studies showed that educational technology applications generally had a positive though modest effect in comparison to traditional methods on student achievement in K–12 classrooms (Cheung, 2013). Turner and Corucher (2013) found that college students' use of traditional media was a significant and viable predictor of both college students' GPAs and their levels of need for cognition. On the other hand, college students' use of socially interactive technologies was wholly unrelated to college students' GPAs and their levels of need for cognition. Junco (2012) also revealed that there was a strong negative relationship between time spent on social media and academic achievement.

Hargittai and Hinnant (2008) stated that young adults are the most highly connected to the Internet. However, it is not reasonable to say that their Internet usage is homogenous, because young adults in the same age range can use the Internet for a wide range of purposes. Their study show that those with higher levels of education and those with a more resource-rich background use the Web for more “capital enhancing” activities, because they engage in more meaningful activities such as career advancement and political participation. Li and Kirkup (2007) investigated differences in the use of, and attitudes toward, the Internet and computers between Chinese and British students as well as gender differences in this cross-cultural context. Significant gender differences were found in both national groups. For example, male students in both countries were more likely to use email and chat rooms than female students. Volman, Eck, Heemskerk, and Kuiper (2005) investigated the accessibility and attractiveness of different types of ICT applications in education for girls and boys. In this respect, gender differences appeared to be small in primary education. However, the girls’ attitudes toward computers seemed to be less positive than that of boys. In addition, girls and boys engaged in different tasks when working together on computers. Furthermore, with respect to secondary education, the two genders also handled ICT tasks differently. In a meta-analysis of gender differences regarding computer-related attitudes and behaviors, males exhibited greater sex-role stereotyping of computers, higher computer self-efficacy, and more positive affect about computers than did females (Whitley, 1997).

The current study is interested in whether or not students’ routine use of technology is related to achievement. The use of technology is twofold: (a) Internet connection duration and (b) technology use aims. This study examines two constructs and gender in relation to achievement in one single study.

The aim of the study

In sum, the above prior studies indicate the relation of gender, motivation, group learning, and technology usage correlation to academic achievement, but these studies also have some limitations. First of all, they have small sample sizes. Thus, it is hard to generalize such small sample sizes to whole population and use common statistical analyses that require predetermined assumptions such as normality, homogeneity of variance, etc. Secondly, the current study tries to overcome these limitations by working with a large number of learners and by classifying students based on their motivation, working style, technology use aims, and Internet connection duration in the same study. Therefore, this study aims to classify university students’ achievement based on three constructs (demographics, study habits, and motivation and familiarity with technology). The following research questions guided the current study:

- RQ1: To what degree do demographics (gender and school year) impact the differences in university students’ GPAs?
- RQ2: To what degree do study habits (motivation type and working style) and gender affect the differences in university students’ GPAs?
- RQ3: To what degree does technology familiarity (weekly Internet connection duration and number of Internet connection aims) and gender impact the differences in university students’ GPAs?

Method

Study group and data collection

Since the aim of the data collection was to reach the most representative sample, this study used a convenience sampling method as heterogeneous samples include a wide variety of characteristics to which the results of the study may be generalizable. The researchers sought out various schools to obtain a heterogeneous sample (Fraenkel & Wallen, 2006; Heppner, Wampold, & Kivlighan, 2008). For this study, random sampling, stratified sampling, or a combination of the two were not used as sampling methods for several reasons. First, some course instructors did not deliver surveys to their students due to their time constraints. Second, some students were not willing to participate in the study. Third, it was difficult to locate some courses or schedule time to administer the survey, etc. In the end, the data were obtained from 2,949 respondents from 11 faculties of a public university in Turkey. The participation ratio from the faculties was 25.97% (n = 766) from the faculty of education, 21.26% (n = 627) from the faculty of engineering, 14.1% (*n* = 415) from the faculty of economics, and administrative sciences, 7.62% (*n* = 225) from the faculty of law, 6.47% (*n* = 191) from the faculty of literature, 6.27% (*n* = 185) from the faculty of medicine, 4.64% (*n* = 137) from the faculty of business, 4.10% (*n* = 121) from the faculty of science, 3.86% (*n* = 114) from faculty of fine arts, 3.25% (*n* = 96) from the maritime faculty and 2.44% (*n* = 72) from the school of nursing.

Instrumentation and manipulation of variables

The data-collection tool is a survey that includes questions about respondents' self-reported GPAs, demographic information, study habits, and familiarity with technology. The GPA is the hypothesized construct and the dependent variable of the study. The dependent variable should exactly reflect the construct to which it may be affected by the independent variables. Accordingly, the researchers asked the students for their cumulative GPAs to determine their achievement in higher education. Self-reported GPAs have also been used by other researchers, and these researchers have reported that official GPAs are correlated with self-reported GPAs (Kuncel, Crede, & Thomas, 2005; Schuman, Walsh, Olson, and Etheridge, 2013)

The independent variables, as determined by the researchers, focused on three main variables of interest, demographics (gender and school year), study habits (working style, motivation types) and technology familiarity (amount of time spent on the Internet, and reasons for Internet use). First, we ascertained gender and university year of respondents were ascertained. Second, the students were asked about their working style (individual or group learning). They were also asked about their motivation to study (extrovert or introvert). Third, the students were asked about their amount of time they spent of the Internet during an average week (0, 1–7 hours, 8–21 hours, 22–35 hours, or more than 36 hours) and reasons for using the Internet (studying, shopping, interaction, doing homework, online banking, social sharing, listening to radio, watching TV, reading newspapers, gaming, Internet surfing, listening to music, watching movies, and other reasons).

Before analyzing the data, we manipulated the independent variables to determine whether a significant difference among the independent variables existed (Heppner at al., 2008). In this study, all independent variables were identified as categorical variables. The university year was limited to four categories (first, second, third, and fourth and above) because the number of the students whose school year exceeded four did not reach the expected ratio. Similarly, the number of hours students spent on the Internet each week was also combined into four categories because there were too few students who never connected to the Internet during the week. This scale was then converted to a categorical variable: 0–3, 4–6, and 7–11. Table 2 shows the number and percentage of the students based on the manipulated levels of independent variables.

Table 2. The participants' demographics, study habits, and familiarity with technology

	Independent variables	Levels	*n*	Percentage (%)
Demographics	Gender	Male	1,315	44.6
		Female	1,634	55.4
	School year	1	674	22.9
		2	804	27.3
		3	919	31.2
		4 and higher	552	18.7
Study habits	Working style	Individual	2,072	70.3
		In a group	876	29.7
	Motivation type	Introvert	1,663	56.4
		Extrovert	1,280	43.4
Technology familiarization	Amount of time spent on the Internet each week	0–7 hours	986	33.4
		8–21 hours	1,035	35.1
		22–35 hours	457	15.5
		More than 36 hours	460	15.6
	Internet connection aims	0–3	282	9.6
		4–6	1,170	39.7
		7–11	1,497	50.8

Data analysis

The CHAID algorithm reveals a tree including meaningful nodes that classify a nominal or ordinal dependent variable (Magidson & Vermunt, 2005). The first CHAID algorithm uses Chi-squire goodness of fit test to identify significant branching regions of independent variables and then merges some levels of independent variables that do not differ in the prediction of the dependent variable (Magidson & Vermunt, 2005). Departing from the classification and regression tree (CART), the CHAID algorithm allows for more than two branching, if there exist significant differences. If the dependent variable is ordinal, the CHAID algorithm uses *F* statistics to decide whether there is another significant predictor of the dependent variable. In the current study, the researchers used ordinal GPA scores and *F* statistics to produce the tree.

When comparing with other inferential statistics methods, the CHAID algorithm has specific advantages. First, while inferential statistical analysis requires the control of several assumptions for statistical tests (Green & Salkind, 2008), the CHAID algorithm does not. Second, the CHAID algorithm makes decisions about dependent variables owing to several terminal nodes in the tree model, while inferential statistics evaluates only whether there exists a significant difference among mean scores of dependent variables in each category of independent variables. Therefore, in this study, we preferred to use the CHAID algorithm to obtain a decision tree that indicated the most significant breaks in the prediction of academic achievement of university students, and accordingly, we aimed to reveal the characteristics of successful and unsuccessful students who are pursuing their higher education.

In addition, we used logistic regression to determine whether the results of the CHAID algorithm were compatible with the results of the logistic regression. Logistic regression aims to predict group membership from a set of independent variables that may be continuous, discrete, dichotomous, or a combination thereof (Tabachnick & Fidel, 2001, p. 517). Logistic regression does not require independent and dependent variables to be continuous variables. In addition, a normality assumption is not necessary to conduct an analysis (Cokluk, Sekercioglu, & Buyukozturk, 2012). In this study, the independent variables are dichotomous and categorical, and the use of logistic regression aims to predict successful university students from a set of their demographics, study habits and technology familiarity.

We determined a dichotomous dependent variable of logistic regression by grouping the first 25% quartile of the students based on their GPAs in one group and coding this group as group 1. The GPAs of the students in group 1 ranged from the lowest grade to a 2.07. Respondents in group 1 could be considered the unsuccessful students. The other respondents were coded as group 2, which means that the GPAs of the students in this group ranged from 2.0701 to the highest grade.

Findings

Classification of GPAs based on gender and year of university

The CHAID algorithm created a tree model with branches for GPAs based on gender and school year. In the tree model, respondents' GPAs were divided by regions for the independent variables and yielded four main results. The first result of the tree reveals that female respondents ($\bar{X}$ = 2.62; SD = 0.58; *n* = 1439) are significantly more successful than male respondents ($\bar{X}$ = 2.33; *SD* = 0.56; *n* = 1180). Second, male respondents in the first year are likely to have the lowest GPAs among the all respondents ($\bar{X}$ = 2.13; *SD* = 0.72; *n* = 254). Similarly, female respondents in first year are likely to have the lowest GPAs among the female respondents. These two results indicate that, at the university, first-year female and male students are more unsuccessful than students attending higher years. The third result suggests that male respondents in the third year are likely to have the highest GPAs among the male respondents. Fourth, female respondents in fourth year and above are likely to have the highest GPAs among all the respondents. These findings are consistent with the other studies that reveal GPAs differ based on gender (Conger & Long, 2010; Turner & Croucher, 2013).

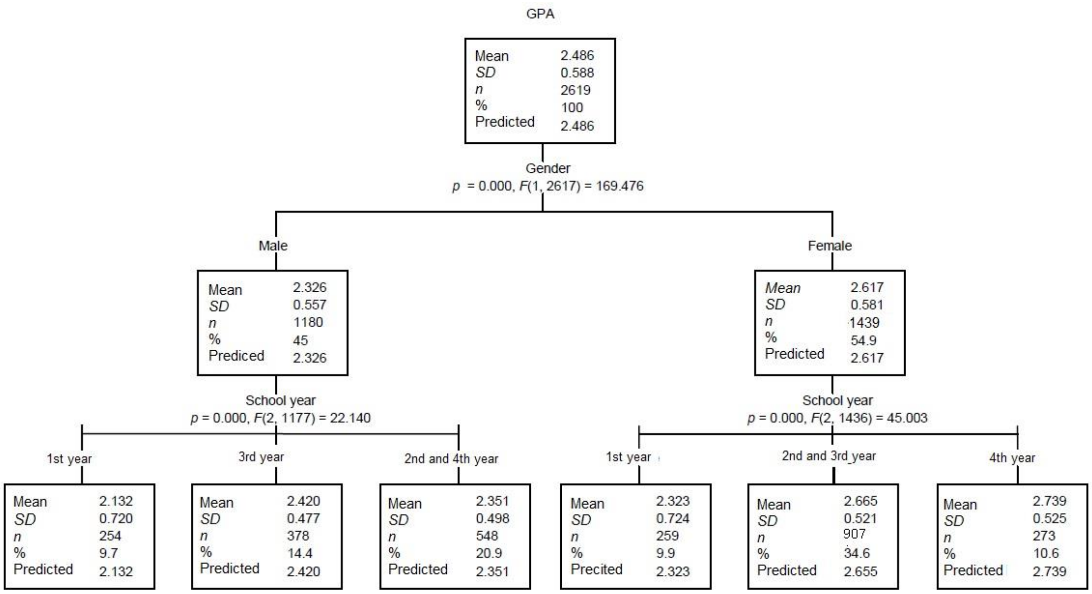

Figure 1. Classification of GPAs based on gender and year of university

Classification of GPAs based on gender and study habits

The second tree model indicates a branching out for GPAs based on motivation type, gender, and working style. The group with the lowest GPAs is the male group, who demonstrate extrovert motivation and prefer learning in a group ($\overline{X}$ = 2.21; *SD* = 0.48; *n* = 207). Next, the group with the highest GPAs is the female group who demonstrate introvert motivation ($\overline{X}$ = 2.67; *SD* = 0.57; *n* = 757). The most valuable result from this tree is that, regardless of gender, those students classified as introvert have higher GPAs than those classified as extrovert. Furthermore, respondents who prefer to study individually have higher GPAs than those who prefer to study in a group.

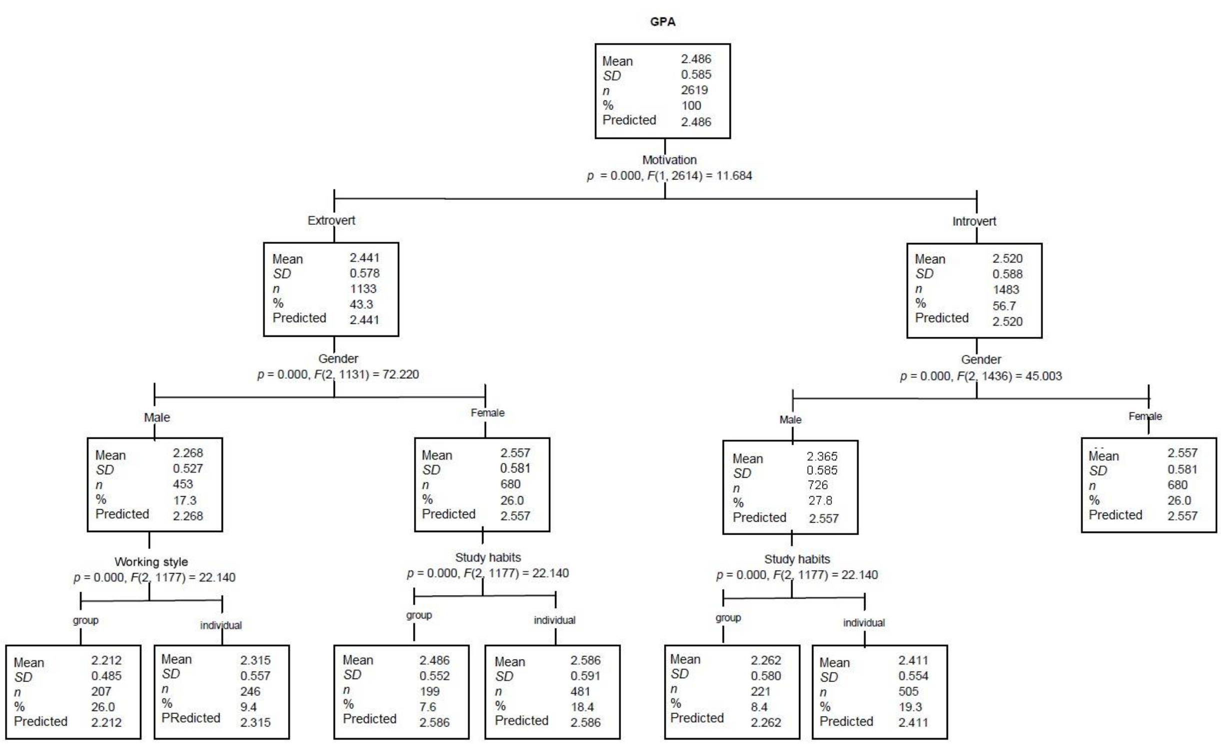

Figure 2. Classification of GPAs based on gender and study habits

Classification of GPAs based on gender and technology familiarity

The third tree model shows a branching out on GPAs based on the amount of time spent on the Internet each week, the number of reasons for using the Internet, and gender. The tree shows that male students using the Internet more than 22 hours a week and using the Internet for up to six reasons have the lowest GPAs among all respondents ($\overline{X}$ = 2.134; *SD* = 0.63; *n* = 123). On the other hand, female respondents using the Internet up to 21 hours a week have the highest GPAs among all respondents ($\overline{X}$ = 2.63; *SD* = 0.57; *n* = 1092). These two results are important, because they suggest that if respondents' use the Internet more than 22 hours a week, their GPAs may decrease.

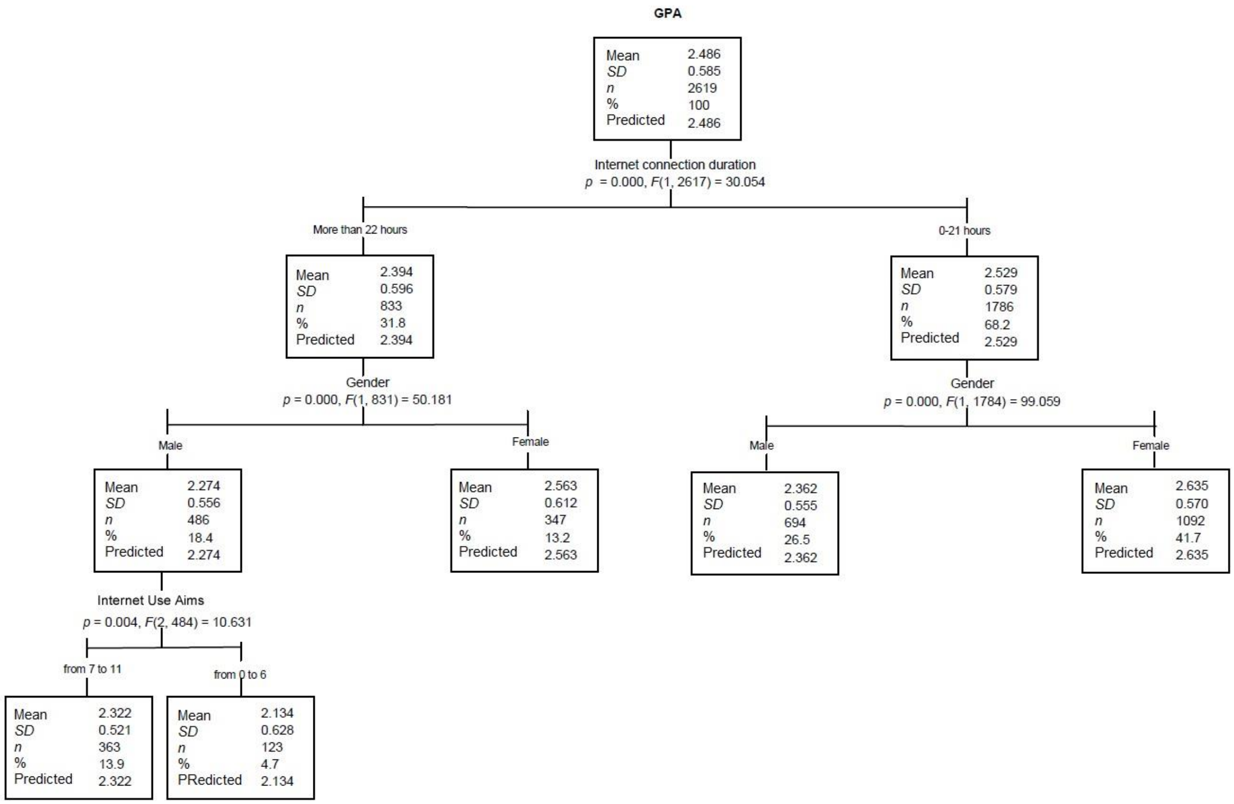

Figure 3. Classification of GPAs based on gender and familiarity with technology

Comparison of CHAID with logistic regression results

Block 1 includes all independent variables and constants that predict whether a student is in the 25th percentile. The prediction is based on the independent variables, which show a total correct classification ratio for the model to be 75.2%. The omnibus test of model coefficients are significant ($\chi^2(11) = 189.194$; $p < 0.05$). The independent variables produce a significantly improved prediction of whether a student is unsuccessful (Acton, Miller, Maltby, & Fullerton, 2009; Cokluk et al., 2012). A Hosmer and Leme test (for goodness of fit) indicated that the model is fit for the data ($\chi^2(8) = 11.35$; $p = 0.18$). When independent variables enter the analysis, an 8% (according to Cox & Snell R^2) or 11% (according to Nagelkerke R^2) variation in academic performance is explained by the independent variables. Table 3 indicates that demographics, study habits, and familiarity with technology have a significant effect on student performance at the university level.

With regard to demographics, the results indicate that male students are 2.33 times more likely to be in the 25th percentile than female students. Similarly, students in their first year are more likely to be in the 25th percentile than second-, third-, and fourth-year students. In addition, a student using the Internet 0–7 hours a week will be approximately 1.5 times more likely to be in the 25th percentile than a student using the Internet more than 35 hours. With regard to motivation, extrovert students will be 1.35 times more likely to be in the 25th percentile than introvert students.

Similar to the CHAID analysis, the logistic regression finds that first-year extroverted male students are more unsuccessful than all other students. This comparison indicates that the CHAID analysis achieves greater classification than other methods because this analysis includes more than one independent variable as well as the levels of these variables in the same analysis.

Table 3. Logistic regression results

		B	*SE*	Wald	*df*	Sig.	Exp(*B*)
Demographics	School year (first-year is ref. category)			71.644	3	.000	
	2	**.819**	**.129**	**40.179**	**1**	**.000**	**2.269**
	3	**1.001**	**.128**	**61.265**	**1**	**.000**	**2.720**
	4	**.867**	**.145**	**35.709**	**1**	**.000**	**2.380**
	Gender (male)	**.844**	**.098**	**74.698**	**1**	**.000**	**2.326**
Technology familiarity	Weekly Internet use (0–7 is ref. category)			12.849	3	.005	
	8–21	-.056	.120	.214	1	.643	.946
	22–35	.208	.145	2.052	1	.152	1.231
	more than 35	**.410**	**.146**	**7.836**	**1**	**.005**	**1.507**
	Internet use aim (1–3 is ref. category)			2.458	2	.293	
	4–6	.198	.173	1.307	1	.253	1.219
	7–11	.269	.174	2.411	1	.120	1.309
Study habits	d13 (group) (individual is ref. category)	.131	.102	1.651	1	.199	1.140
	d15 (extrovert) (introvert is ref. category)	**.301**	**.096**	**9.904**	**1**	**.002**	**1.351**
	Constant	−.831	.233	12.739	1	.000	.436

Discussion

This study reveals relationships involving university students' demographics, study habits, and familiarity with technology are correlated with their self-reported GPAs. Different from available studies, this study indicates that inferences can be made based on several terminal nodes taken from the tree model, thus making it easier to identify significant breaks that involve one or more independent variables. The results of this study show that gender, study habits, and familiarity with technology are important factors that may explain university students' achievement.

Consistent with the findings of similar studies, the results of this study also indicate that female students are more successful than male students (Conger & Long, 2010; Veenstra & Kuyper, 2004; Sarıer, 2010). Conger and Long (2010) revealed that male students earned lower GPAs and fewer credits in their first semester of college, largely because they arrived with lower high-school grades, while female students' better high-school grades explained some of the gender disparity in performance. Different from available studies, the findings of the current study further show that male students in the first year are likely to have the lowest GPAs among all respondents. This result suggests that male students are at greater risk of being unsuccessful academically than female students because they are behind their female counterparts in each school year. This result is also consistent with the extant literature (Stewart & Levin, 2001). Similarly, female students in first year are likely to have the lowest GPAs among all female respondents. That is, the current study indicates that both male and female students may earn lower GPAs in the first academic year because it is their first encounter with the higher education. In Turkey, prior to attending higher education, students graduate from general high schools or vocational/technical high schools (Aksit, 2007). Only students who receive the best scores on the university entrance exams can then enroll in schools of medicine, dentistry, political science, etc. This suggests that new incoming students do not have time to adapt to university life after leaving high school. The literature illustrates that the reason for the lower GPAs in first year might be due to several reasons, such as communication problems that the students encounter, differences in teaching methodologies and learning strategies at the university level, the physical environment, and a lack of awareness regarding their personal study skills (Topcu & Uzundumlu, 2012). Furthermore, the findings indicate that, for both male and female students, GPAs increase as their progress with each year of university.

This classification study shows that female students who are introvertedly motivated have the highest GPAs, while males who are extrovertedly motivated having the lowest GPAs. Consistent with the existing literature, Ayub (2010) also found that female students were more intrinsically motivated, while male students were more extrinsically motivated. Regardless of gender, however, students who are classified as an introvert have higher GPAs than those who are found to be an extrovert. Based on previous research, it can be concluded that intrinsic motivation has a positive effect on achievement (Areepattamannil et al., 2011; Eymur & Geban, 2012; Lynch, 2006). In terms of working habits (individual or group learning), students who prefer to study individually have higher GPAs than their counterparts who prefer group study. Therefore, it is important to examine our students' group processing as students engage with their peers while learning and studying in a group (Johnson & Johnson, 2009). With respect to learning groups, if the teacher or researcher ensures that every group member works actively in the construction of knowledge, scaffolds other group members, and works to the best of their ability, the performance and achievement of the group and of each member may increase (Goodsell, Maher, & Tinto, 1992; Vygotsky, 1978). Conversely, if there are deficits in the group work or if group members do not know how to communicate their knowledge to others, the group as a whole and the individual members of the group cannot attain their desired goals.

Given the above findings, we recommend that well-designed group work (which is very important for higher education because approximately one-third of the students prefer to learn in a group) be incorporated in the curricula. Furthermore, the use of small group design using technology should be supported by higher education institutions because there is considerable positive published evidence that supports its implementation (Bennett, Bishop, Dalgarno, Waycott, & Kennedy, 2012; Laru, Naykki, & Jarvela, 2012; Li, Helou, & Gillet, 2012). Apart from these available studies, which focus on either motivation or group learning, the current study examines motivation type, group learning, and gender in one study. The findings indicate that achievement of extrovert male students preferring learning in a group is lower than introvert male students preferring learning in a group. The similar result is not meaningful for female students.

Finally, the results illustrate that Internet usage totaling more than 22 hours a week may result in decreased GPAs and that technology may have a detrimental effect on school work. Studies on the effect of ICT on academic performance provide more evidence that a high amount of technology use causes some problems for students, such as lower achievement and Internet addiction (Chou & Hsiao, 2000; Chou, Condron, & Belland, 2005; Junco, 2012). While net-generation students are capable of increased multitasking, this multitasking may cause academic delays of which they are not aware (Bowman, Levine, Waite, & Gendron, 2010; Junco & Cotten, 2012). Therefore, it is vital to inform students about how to use the Internet effectively and in such a way that it contributes to their success in higher education. The current study, however, reveals that Internet use of up to 21 hours, which appears to be a critical point, can explain university students' higher GPAs, as university students tend to use the Internet for academic purposes up to this point. Increasing services available on the Internet, such as academic libraries, online certifications, and university communities on social media, allow students to spend more time on the Internet (Hendrix, Chiarella, Hasman, Murphy, & Zaphron, 2009). Most of our sample includes Net generation students and, as such, they have higher level computer skills and more experience with social media than did students 10 years ago (Frand, 2000; Oblinger & Oblinger, 2005). As a result of these factors, higher education curricula should incorporate the effective use of technology, as also emphasized by another study and instructors should adapt their lessons according to the characteristics of students of the Net Generation.

The researchers of this study also suggest that other researchers should focus on more pedagogical aspect of this topic in the future. We certainly think and believe that other researchers should study professions such as engineering or teacher education. Therefore, in addition to gender and university level, university profession should be added to the study. With regard to study habits, self-efficacy, students' satisfaction with the education, and their interest to the profession may be correlated with their achievement. Lastly, an ICT literacy construct, which may include "information technology, mobile technology, and communication technology literacies," can be added to the study. This construct will let researchers to see which technology we should select while designing a course in university level.

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