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Araştırma Makalesi / Research Article

Application of Data Mining Algorithms and Statistical Hypothesis Testing to Analyze Problematic Internet Use among University Students

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Abstract

This study aims to understand university students' internet usage habits and whether these habits are associated with certain sociodemographic and behavioral variables. Data were obtained from the General Problematic Internet Use Scale 2 (GPIUS2) survey, administered to undergraduate students from eight programs at a state university in Türkiye, and analyzed using the Apriori Association Rule Mining Algorithm and statistical hypothesis testing. The responses from 217 students were analyzed to gain insights into their problematic internet use habits. Analysis conducted using WEKA software identified significant associations with the "Mood Regulation" dimension, particularly among male students and those with high GPAs. Additionally, communication-related smartphone usage was found to be associated with the "Negative Outcomes" dimension. The research findings also reveal that university students' problematic internet use is statistically associated with the program they are enrolled in, marital status, self-reported daily smartphone usage, primary reason for smartphone use, and self-reported addiction. This study contributes a new perspective to the application of data mining techniques in social sciences and educational research, providing valuable insights into the relationships between internet usage habits and problematic usage, thus laying a foundation for future research.

Keywords: Association Rule Mining, Data Mining, Technological Addiction Analysis, Problematic Internet Use, University Students.

Üniversite Öğrencilerinde Problemli İnternet Kullanımını Analiz Etmek İçin Veri Madenciliği Algoritmalarının ve İstatistiksel Hipotez Testinin Uygulanması

Öz

Bu çalışma, üniversite öğrencilerinin internet kullanım alışkanlıklarını ve bu alışkanlıkların belirli sosyodemografik ve davranışsal değişkenlerle ilişkili olup olmadığını anlamayı amaçlamaktadır. Veriler, Türkiye'deki bir devlet üniversitesinin sekiz programında öğrenim gören lisans öğrencilerine uygulanan Genelleştirilmiş Problemli İnternet Kullanımı Ölçeği 2 (GPIUS2) anketinden elde edilmiş ve Apriori Birliktelik Kuralı Madenciliği Algoritması ile istatistiksel hipotez testleri kullanılarak analiz edilmiştir. Toplamda 217 öğrencinin yanıtları, problemli İnternet kullanım alışkanlıklarına dair sonuçlar elde etmek amacıyla analiz edilmiştir. WEKA yazılımı kullanılarak yapılan analizler, özellikle erkek öğrenciler ve yüksek not ortalamasına sahip öğrenciler arasında "Duygu Düzenleme" boyutuyla anlamlı ilişkiler tespit etmiştir. Ayrıca, iletişim amaçlı telefon kullanımının "Olumsuz Sonuçlar" boyutuyla ilişkili olduğu bulunmuştur. Araştırmanın istatiksel hipotezlere ilişkin bulguları ise, üniversite öğrencilerinin problemli internet kullanımının kayıtlı oldukları program, medeni durum, kendi bildirdikleri günlük akıllı telefon kullanımı, akıllı telefon kullanımının birincil nedeni ve kendi bildirdikleri bağımlılık durumu ile istatistiksel olarak ilişkili olduğunu ortaya koymaktadır. Bu çalışma, veri madenciliği tekniklerinin sosyal bilimler ve eğitim araştırmalarında uygulanmasına yeni bir perspektif kazandırarak, internet kullanım alışkanlıkları, problemli İnternet kullanım ve sosyodemografik özellikler ve akademik başarı arasındaki ilişkiler hakkında kapsamlı çıkarımlar sunmakta ve böylelikle gelecekteki araştırmalara temel oluşturmaktadır.

Anahtar Kelimeler: Birliktelik Kuralı Madenciliği, Veri Madenciliği, Teknoloji Bağımlılığı Analizi, Problemli İnternet Kullanımı, Üniversite Öğrencileri.

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1. Introduction

Research on problematic internet use among students is increasingly becoming a significant concern due to its negative impact on academic achievement (Fatehi et al., 2016; Gorgich et al., 2017). Contributing factors include GPA, field of study, and the availability of school-based Internet access (Mrayyan et al., 2022). Gender also plays a significant role, with men being more vulnerable to symptoms of problematic internet use (Baloğlu et al., 2020). For instance, Vigna-Taglianti et al. (2017) found that problematic internet use is more prevalent among male students than their female counterparts. To ensure students' long-term mental and emotional well-being, it is essential to address problematic internet use and its associated psychological, social, and academic implications (Fatehi et al., 2016; Gorgich et al., 2017).

Problematic internet use has been studied using different methods of data collection and analysis. Data collection instruments to explore problematic internet use included but not limited to the use of questionnaires, interviews, systematic reviews, observation. Data were analyzed through descriptive and inferential statistics (Derbyshire et al., 2013), case studies (Sanchez Vega et al., 2016), content and thematic analyses (Özparlak et al., 2023; Rollo et al., 2023). The present study is unique in this sense since it not only uses descriptive and inferential statistics but also uses data mining to provide insights into university students' internet usage habits, their tendency to problematic internet use and how their GPAs affected by problematic internet use.

Data mining encompasses a range of techniques and methods used to uncover hidden patterns and relationships within large datasets (Han and Kamber, 2001). These techniques are applied across various fields to extract valuable insights. One such technique, association rule mining, is a significant subfield of data mining and is frequently used in the retail sector to determine the likelihood of products being purchased together in customer shopping baskets.

Association rule mining aims to discover itemsets that frequently occur together in datasets. This technique is widely used in the process known as market basket analysis (Han and Kamber, 2001). Market basket analysis examines customer purchasing habits to identify which products are bought together. This information can be used to optimize sales strategies, increase cross-selling opportunities, and enhance customer satisfaction. Among the most popular and frequently used algorithms in association rule mining is the Apriori algorithm.

The Apriori algorithm, introduced by Agrawal and Srikant in 1994, is an efficient method for discovering frequent itemsets in large datasets (Agrawal and Srikant, 1994). This algorithm scans the entire dataset for all possible itemsets and selects those that meet a specified support threshold. It then derives association rules among these itemsets and evaluates them based on their confidence and support values.

Using the Apriori algorithm for association rule extraction can also be applied to problematic internet use survey data. In this context, relationships between students' internet usage habits and whether these habits become a risk factor for problematic internet use can be explored. The literature contains various studies where association rule mining using the Apriori algorithm has provided significant findings. For example, in the health sector, relationships between patients' symptoms and diseases have been examined (Bhardwaj et al., 2018a; Bhardwaj et al., 2018b), and in the education sector, relationships between students' academic achievements and study habits have been analyzed (Liu et al., 2019a; Liu et al., 2019b). However, the analysis of survey data on problematic internet use among university students using the Apriori algorithm, alongside descriptive and inferential statistics, remains a relatively underexplored topic. This study aims to address this gap in the literature by drawing on data from students across a wide range of undergraduate programs.

1.1. Use of the Apriori Algorithm in the Literature

The Apriori algorithm has been employed in various studies within the education sector, primarily aiming to investigate relationships between students' academic performance, learning behaviors, and study habits.

1. **Academic Achievement and Study Habits:** Liu et al. (2019b) used the Apriori algorithm to examine the relationships between students' course achievements and their study habits. This study aimed to determine the study methods associated with high academic performance and under what conditions these methods are effective. The findings have helped educators develop more effective study strategies for students.
2. **Student Behaviors and Performance Analysis:** Zhang et al. (2020) used the Apriori algorithm to analyze the relationships between university students' learning behaviors and academic performance. This study identified the resources and methods students use while studying and how these behaviors relate to academic success. These findings provide valuable insights for developing educational technologies and personalized learning environments.
3. **E-Learning Platforms:** Chen et al. (2018) applied the Apriori algorithm to analyze interaction data from students on e-learning platforms. This study examined which types of content and activities students engage with more and the impact of these interactions on learning outcomes. The results have been used to improve the design of e-learning platforms and offer more effective learning experiences for students.

These studies demonstrate that the Apriori algorithm can reveal significant relationships and patterns concerning student behaviors and academic performance. Analyzing GPIUS2 survey data will introduce a new dimension to the use of this algorithm in social sciences and educational research.

1.2. Objective and Contributions of the Study

The primary objective of this study is to examine the relationship between university students' problematic internet use and their sociodemographic and behavioral characteristics (age, gender, program enrolled in, year of study, marital status, having an internet plan, self-reported daily smartphone usage, primary reason for smartphone use, self-reported addiction, monthly average income, and monthly average expenditure), as well as their academic performance. Specifically, this study aims to identify possible relationships and patterns in university students' internet usage, examining how these are influenced by their sociodemographic and behavioral characteristics, as well as their academic performance, through the application of association rules. The study also statistically tests the central hypothesis that problematic internet use among university students varies based on their sociodemographic and behavioral characteristics, as well as their academic performance.

The contributions of this study to the literature are threefold. First, the analysis of GPIUS2 survey data using the Apriori algorithm represents a relatively novel application in this field, providing a valuable reference for future research. Second, the study offers crucial insights into the impact of various sociodemographic and behavioral variables on students' problematic internet use, examining the background of this issue by identifying potential risk factors within a diverse sample of undergraduate students. Finally, it serves as an exemplar of how data mining techniques can be effectively applied in social sciences and educational research.

2. Materials and Methods

The research methodology systematically addresses the data collection and analysis processes, aiming to ensure the reliability and validity of the findings obtained.

2.1. Dataset

The dataset for this study was collected through a survey form based on the GPIUS2 (Caplan, 2010), administered to students from three faculties at a state university in southern Turkey, with responses gathered via Google Forms. The GPIUS2 comprises 15 items distributed across five subscales: Preference for Online Social Interaction (POSI), Mood Regulation, Cognitive

Preoccupation, Compulsive Internet Use, and Negative Outcomes (Caplan, 2010). Each subscale includes three items. Respondents rate their agreement with each item on a scale from 1 ("definitely disagree") to 8 ("definitely agree"), resulting in possible total scores ranging from 15 to 120. Higher GPIUS2 scores indicate more severe problematic internet use. The overall reliability of the GPIUS2 was reported to be $\alpha = .91$ (Caplan, 2010). The survey evaluates students' internet usage habits and the social and psychological impacts of these habits, along with certain demographic information. The survey results include scores measuring each student's self-reported problematic internet usage.

2.2. Data Preparation

The survey was administered to 226 students between May 2022 and June 2023. Following data collection, the survey responses were meticulously cleaned to address missing or erroneous data, ensuring the dataset's integrity. During this process, nine students' responses were excluded from the analysis due to significant missing data. As a result, the final analysis included data from 217 students. Each survey question was processed as categorical data determining a specific internet usage habit or behavior of the student. These categorical data were converted into a format suitable for association rule extraction using the Apriori algorithm.

2.3. Participants

After excluding the data of participants who did not meet the study requirements, a total of 217 responses were subjected to data rule mining analyses. The participants' ages ranged from 19 to 32, with a mean of 22.18 (*SD* = 1.78). Of the 217 participants, the majority (95.4%) identified as single, while a minority (4.6%) reported being married. To assess academic achievement, students were asked to provide their grade point average and the participants' mean GPA was 2.66 (*SD* = .47). Among the participants, only three students (1.4%) reported not using an internet plan. In summary, data from the responses of 217 students were initially subjected to data rule mining analyses. Descriptive statistics regarding the participants' profiles are presented in Table 1.

Table 1. Participants' General Characteristics (N = 217)

Variable	*f*	%
Gender		
Male	96	44.2
Female	121	55.8
Program enrolled in		
Business Administration	22	10.1
Industrial Engineering	27	12.4
International Relations	10	4.6
International Trade and Finance	63	29
Management Information Systems	50	23
Political Science and Public Administration	26	12
Tourism Management	2	0.9
Translation and Interpreting	17	7.8
Year of study		
First year	47	21.7
Second year	67	30.9
Third year	53	24.4
Fourth Year	50	23.0
Self-reported daily smartphone usage		
0-2 hours	41	18.9
2-4 hours	83	38.2
4-6 hours	67	30.9
More than 6 hours	26	12.0
Primary reason for smartphone use		
Social media	89	41.0
Making calls and sending texts	75	34.6
Accessing information	35	16.1
Learning and education	9	4.1
Entertainment and photography	9	4.1
Self-reported addiction		
None	120	55.3
Smoking	57	26.3
Alcohol	4	1.8
Smartphone	36	16.6
Monthly average income		
TRY 1 to TRY 5000	192	88.5
TRY 5,001 to TRY 10,000	18	8.3
TRY 10,001 or more	7	3.2
Monthly average expenditure		
TRY 1 to TRY 5000	202	93.1
TRY 5,001 to TRY 10,000	13	6.0
TRY 10,001 or more	2	.9

2.4. Apriori Algorithm

The Apriori algorithm (Agrawal and Srikant, 1994) was used to extract frequent itemsets and association rules from the dataset. The basic working principle of the algorithm can be summarized in the following steps:

The algorithm begins with individual items and generates combinations of these items, selecting those that meet a specified support threshold as candidate itemsets. It then calculates the frequency with which each candidate itemset appears in the dataset, referring to this value as support. Using the given support threshold (minimum support threshold), frequent itemsets are identified. Once these frequent itemsets are identified, association rules among them are extracted and evaluated based on their confidence and support values (Agrawal and Srikant, 1994). Confidence represents the likelihood of one itemset occurring given the presence of another itemset (Keleş and Kaya, 2014). The algorithm then uses the frequent itemsets found in the previous step to create larger itemsets and examines the relationships among them. This process is repeated until all itemsets that meet the specified support and confidence thresholds are found. The extracted association rules are further evaluated based on their confidence, support, and lift values, which are used to determine the validity and significance of the rules (Agrawal and Srikant, 1994).

The Apriori algorithm and association rule mining have significant applications not only in the retail sector but also in various other fields such as in healthcare sector it can be used to discover relationships between patients' symptoms and treatment methods or improving diagnosis and care plans (Bhardwaj et al., 2018a). In education, for example, these techniques reveal links to examine relationships between students' academic achievements and learning behaviors guiding educators in refining teaching strategies (Liu et al., 2019a). Similarly, in e-commerce, they analyze customers' purchasing behaviors to create personalized recommendations and marketing strategies (Das et al., 2021). In this study the Apriori algorithm is used for education sector.

Class Association Rules (CAR), which performs data mining by focusing on a specific subset of association rules are used in this study instead of general association rules for the integration of data in order to ensure the selection of the most interesting rules from the entire set of possible rules (Liu et al., 1998).

2.5. Data Analysis

SPSS Statistics was employed to analyze student data based on their scale item responses. Internal consistency for the composite scale was calculated, and in the present study, Cronbach's alpha was found to be 0.92. The distributions of responses on the 15 items were examined to assess normality. To investigate the relationship between sociodemographic and behavioral variables and problematic internet use, t-tests, one-way analysis of variance, Mann-Whitney U and Kruskal-Wallis tests were performed.

WEKA (Waikato Environment for Knowledge Analysis) software can be used to apply the Apriori algorithm and perform analyses. WEKA is an open-source software that facilitates the application of data mining and machine learning algorithms (Witten et al., 2016). For this study, minimum support was set at 0.01 value and minimum confidence at 0.9 value.

3. Results and Discussion

The extracted association rules were analyzed to identify meaningful relationships. These relationships revealed possible connections between students' internet usage habits and problematic internet usage. The analysis results were evaluated both quantitatively and qualitatively and compared with findings from existing literature.

Some of the results obtained from the rules derived with a minimum support of 0.05 value and a minimum confidence of 0.80 value in WEKA are shown in Table 2.

Table 2. Best Extracted Rules.

Rule ID	Extracted Rules	Class	Confidence
1	gender=2 program=2 reported addiction=2	subscale=mood regulation	conf:(1)
2	gender=2 program=2 internet plan=1 reported addiction=2	subscale=mood regulation	conf:(1)
3	gender=2 program= 2 marital status=1 reported addiction=2	subscale=mood regulation	conf:(1)
4	gender=1 program=2 reported addiction=1 purpose of use=1	subscale=mood regulation	conf:(1)
5	gender=2 program=2 monthly average income=1 reported addiction=2	subscale=mood regulation	conf:(1)
6	gender=1 program=2 internet plan=1 reported addiction=1 purpose of use=1	subscale=mood regulation	conf:(1)
7	reported addiction=2 GPA=low	subscale=mood regulation	conf:(1)
8	gender=1 program=4 year=2	subscale=mood regulation	conf:(1)
9	year=2 daily smartphone usage=3 GPA=high	subscale=mood regulation	conf:(1)
10	Internet plan=1 reported addiction=2 GPA=low	subscale=mood regulation	conf:(1)
11	marital status = 1 reported addiction = 2 GPA=low	subscale=mood regulation	conf:(1)
12	monthly average income=1 reported addiction=2 GPA=low	subscale=mood regulation	conf:(1)
13	program=2 marital status=1 daily smartphone usage=3 GPA=high	subscale=mood regulation	conf:(1)
14	program=2 monthly average income=1 daily smartphone usage=3 GPA=high	subscale=mood regulation	conf:(1)
15	program=2 monthly average expenditure=1 daily smartphone usage=3 GPA=high	subscale=mood regulation	conf:(1)
16	year=2 internet plan=1 daily smartphone usage=3 GPA=high	subscale=mood regulation	conf:(1)
17	gender=1 age=19-22 program=4 year=2 internet plan=1 monthly average expenditure=1	subscale=mood regulation	conf:(1)
18	gender=1 age=19-22 year=2 internet plan=1 reported addiction=1 daily smartphone usage=3	subscale=mood regulation	conf:(1)
19	gender = 1 age = 19-22 year=2 marital status = 1 reported addiction=1 daily smartphone usage=3	subscale=mood regulation	conf:(1)
20	gender=1 age=19-22 year=2 monthly average expenditure=1 reported addiction=1 daily smartphone usage=3	subscale=mood regulation	conf:(1)
21	gender=1 program=2 year=2 reported addiction=1 purpose of use=1	subscale=mood regulation	conf:(1)
22	program=4 year=2 internet plan=1 marital status=1 monthly average expenditure=1 reported addiction=1	subscale=mood regulation	conf:(1)
23	year=1 internet plan=1 marital status=1 monthly average income=1 reported addiction=2 GPA=low	subscale=mood regulation	conf:(1)
24	gender=2 program=7 purpose of use=2	subscale=negative outcomes	conf:(1)

25	program=7 monthly average income=1 purpose of use=2	subscale=negative outcomes	conf:(1)
26	gender=1 program=4 year=2 internet plan=1 marital status=1 monthly average expenditure=1 reported addiction=1	subscale=mood regulation	conf:(1)
27	gender=2 age=23-32 program=7 purpose of use=2	subscale=negative outcomes	conf:(1)
28	gender=2 program=2 internet plan=1 marital status=1 monthly average income=1 monthly average expenditure=1 purpose of use=2	subscale=mood regulation	conf:(1)
29	age=19-22 program=4 year=2 internet plan=1 marital status=1 monthly average expenditure=1 reported addiction=1	subscale=mood regulation	conf:(1)
30	years=4 monthly average expenditure=1 purpose of use=1 daily smartphone usage=2 GPA=high	subscale=mood regulation	conf:(1)
31	gender=2 year=2 internet plan=1 marital status=1 purpose of use=1 daily smartphone usage=2	subscale=POSI	conf:(1)
32	age=19-22 program=3 year=1 internet plan=1 marital status=1 reported addiction=1	subscale=POSI	conf:(1)
33	age=23-32 monthly average income=1 monthly average expenditure=1 purpose of use=1 daily smartphone usage=2 GPA=high	subscale=mood regulation	conf:(1)
34	program=1 year=2 internet plan=1 marital status=1 monthly average income=1 purpose of use=1	subscale=mood regulation	conf:(1)
35	reported addiction=4 daily smartphone usage=2 GPA=mid	subscale=compulsive internet use	conf:(1)
36	Internet plan=1 reported addiction=4 daily smartphone usage=2 GPA=mid	subscale=compulsive internet use	conf:(1)
37	marital status=1 reported addiction=4 daily smartphone usage=2 GPA=mid	subscale=compulsive internet use	conf:(1)
38	monthly average expenditure=1 reported addiction=4 daily smartphone usage=2 GPA=mid	subscale=compulsive internet use	conf:(1)
39	program=2 monthly average expenditure=1 reported addiction=1 daily smartphone usage=1 GPA=high	subscale=POSI	conf:(1)
40	year=4 internet plan=1 marital status=1 daily smartphone usage=1 GPA=high	subscale=POSI	conf:(1)
41	year=4 marital status=1 monthly average expenditure=1 daily smartphone usage=1 GPA=high	subscale=POSI	conf:(1)
42	year=4 marital status=1 reported addiction=1 daily smartphone usage=1 GPA=high	subscale=POSI	conf:(1)
43	Internet plan=1 monthly average expenditure=1 reported addiction=4 daily smartphone usage=2 GPA=mid	subscale=compulsive internet use	conf:(1)
44	gender=2 age=19-22 year=2 marital status=1 purpose of use=1 daily smartphone usage=2	subscale=POSI	conf:(1)
45	program=4 reported addiction=2 daily smartphone usage=3	subscale=cognitive preoccupation	conf:(1)
46	program=4 internet plan=1 reported addiction=2 daily smartphone usage=3	subscale=cognitive preoccupation	conf:(1)
47	program=8 year=3 monthly average expenditure=1 purpose of use=3	subscale=mood regulation	conf:(1)
48	program=4 internet plan=1 monthly average expenditure=1 reported addiction=2 daily smartphone usage=3	subscale=cognitive preoccupation	conf:(1)
49	program=4 marital status=1 monthly average expenditure=1 reported addiction=2 daily smartphone usage=3	subscale=cognitive preoccupation	conf:(1)
50	program=4 internet plan=1 marital status=1 monthly average expenditure=1 reported addiction=2 daily smartphone usage=3	subscale=cognitive preoccupation	conf:(1)
51	program=8 year=3 internet plan=1 marital status=1 monthly average expenditure=1 purpose of use=3	subscale=mood regulation	conf:(1)
52	year=1 marital status=1 monthly average income=1 reported addiction=2 purpose of use=2 GPA=low	subscale=mood regulation	conf:(1)
53	year=2 internet plan=1 marital status=1 monthly average income=1 purpose of use=3 GPA=low	subscale=mood regulation	conf:(1)
54	year=3 monthly average income=1 monthly average expenditure=1 reported addiction=4 purpose of use=1 GPA=mid	subscale=compulsive internet use	conf:(1)
55	year=4 internet plan=1 marital status=1 monthly average income=1 daily smartphone usage=1 GPA=high	subscale=POSI	conf:(1)
56	gender=1 age=23-32 program=1 year=4 internet plan=1 reported addiction=1 daily smartphone usage=3	subscale=POSI	conf:(1)
57	gender=1 program=1 year=4 internet plan=1 marital status=1 reported addiction=1 daily smartphone usage=3	subscale=POSI	conf:(1)
58	age=23-32 program=2 internet plan=1 marital status=1 monthly average income=1 monthly average expenditure=1 GPA=high	subscale=mood regulation	conf:(0.9)

59	program=2 internet plan=1 marital status=1 monthly average income=1 monthly average expenditure=1 purpose of use=1 daily smartphone usage=3	subscale=mood regulation	conf:(0.9)
60	gender=1 age=19-22 year=2 internet plan=1 marital status=1 monthly average income=1 monthly average expenditure=1 daily smartphone usage=3	subscale=mood regulation	conf:(0.9)

If a general evaluation needs to be made about the meaning of some of the rules shown in Table 1, for example;

Rule 1:

Attributes: Gender = 2 (Male), Program enrolled in = 2 (International Trade and Finance), Self-reported addiction = 2 (Smoking)

Result: Sub-dimension= Mood Regulation

Confidence: 1 (100%)

Explanation: For individuals who are male, studying in the International Trade and Finance department, and have an addiction to smoking, 100% belong to sub-dimension 2, which corresponds to the dimension Mood Regulation.

Rule 9:

Attributes: Year of study = 2, Average daily smartphone usage frequency = 3 (4-6 hours), GPA = High (2.76 and above)

Result: Sub-dimension= Mood Regulation

Confidence: 1 (100%)

Explanation: For second-year students who use their smartphones for 4-6 hours daily and have a high GPA (2.76 and above), 100% belong to sub-dimension 2, which corresponds to the dimension Mood Regulation.

Rule 13:

Attributes: Program enrolled in = 2 (International Trade and Finance), Marital status = 1 (Single), Average daily smartphone usage frequency = 3 (4-6 hours), GPA = High (2.76 and above)

Result: Sub-dimension = Mood Regulation

Confidence: 1 (100%)

Explanation: For single students in the International Trade and Finance department who use their smartphones for 4-6 hours daily and have a high GPA (2.76 and above), 100% belong to sub-dimension 2, which corresponds to the dimension Mood Regulation.

Rule 20:

Attributes: Gender = 1 (Female), Age = 19-22, Year of study = 2, Monthly average expenditure = 1 (TRY 1 to TRY 5000), Self-reported addiction = 1 (None), Average daily smartphone usage frequency = 3 (4-6 hours)

Result: Sub-dimension = Mood Regulation

Confidence: 1 (100%)

Explanation: For females aged 19-22, in their second year, with low monthly expenditures, no existing addiction, and who use their smartphones for 4-6 hours daily, 100% belong to sub-dimension 2, which corresponds to the dimension Mood Regulation.

Rule 22:

Attributes: Program enrolled in = 4 (Political Science and Public Administration), Year of study = 2, Internet plan = 1 (Yes), Marital status = 1 (Single), Monthly average expenditure = 1 (TRY 1 to TRY 5000), Self-reported addiction = 1 (None)

Result: Sub-dimension= Mood Regulation

Confidence: 1 (100%)

Explanation: For single second-year students in the Political Science and Public Administration department with an internet package and low monthly expenditures and no existing addiction, 100% belong to sub-dimension 2, which corresponds to the dimension Mood Regulation.

Rule 24:

Attributes: Gender = 2 (Male), Program enrolled in = 7 (Translation and Interpreting), Primary reason for smartphone use = 2 (Making calls and sending texts)

Result: Sub-dimension = Negative Outcomes

Confidence: 1 (100%)

Explanation: For males in the Translation and Interpreting department who use their smartphones primarily for making calls and sending texts, 100% belong to sub-dimension 5, which corresponds to the dimension Negative Outcomes.

Rule 25:

Attributes: Program enrolled in = 7 (Translation and Interpreting), Monthly average income=1 (TRY 1 to TRY 5000), Primary reason for smartphone use = 2 (Making calls and sending texts)

Result: Sub-dimension = Negative Outcomes

Confidence: 1 (100%)

Explanation: For students in the Translation and Interpreting department with low monthly income and who use their smartphones primarily for making calls and sending texts, 100% belong to sub-dimension 5, which corresponds to the dimension Negative Outcomes.

Rule 27:

Attributes: Gender = 2 (Male), Age = 23-32, Program enrolled in = 7 (Translation and Interpreting), Primary reason for smartphone use = 2 (Making calls and sending texts)

Result: Sub-dimension = Negative Outcomes

Confidence: 1 (100%)

Explanation: For males aged 23-32 in the Translation and Interpreting department who use their smartphones primarily for making calls and sending texts, 100% belong to sub-dimension 5, which corresponds to the dimension Negative Outcomes.

Rule 31:

Attributes: Gender = 2 (Male), Year of study = 2, Internet plan = 1 (Yes), Marital status = 1 (Single), Primary reason for smartphone use = 1 (Social media), Average daily smartphone usage frequency = 2 (2-4 hours)

Result: Sub-dimension = Preference for Online Social Interaction

Confidence: 1 (100%)

Explanation: For single males in their second year with an internet package, who use their smartphones for a specific purpose and for more than 2 hours daily, 100% belong to sub-dimension 1, which corresponds to the dimension Preference for Online Social Interaction.

Rule 33:

Attributes: Age = 23-32, Monthly average income = 1 (TRY 1 to TRY 5000), Monthly average expenditure = 1 (TRY 1 to TRY 5000), Primary reason for smartphone use = 1 (Social media), Average daily smartphone usage frequency = 2 (2-4 hours), GPA = High (2.76 and above)

Result: Sub-dimension = Mood Regulation

Confidence: 1 (100%)

Explanation: For individuals aged 23-32 with low monthly income and expenditure, who use their smartphones primarily for social media, for 2-4 hours daily, and have a high GPA (2.76 and above), 100% belong to sub-dimension 2, which corresponds to the dimension Mood Regulation.

Rule 35:

Attributes: Self-reported addiction = 4 (Smartphone), Average daily smartphone usage frequency = 2 (2-4 hours), GPA = Mid (2.01-2.75)

Result: Sub-dimension = Compulsive Internet Use

Confidence: 1 (100%)

Explanation: For individuals with high addiction, who use their smartphones for more than 2 hours daily and have a medium GPA, 100% belong to sub-dimension 4, which corresponds to the dimension Compulsive Internet Use.

Rule 38:

Attributes: Monthly average expenditure = 1 (TRY 1 to TRY 5000), Self-reported addiction = 4 (smartphone), Average daily smartphone usage frequency = 2 (2-4 hours), GPA = Mid (2.01-2.75)

Result: Sub-dimension = Compulsive Internet Use

Confidence: 1 (100%)

Explanation: For individuals with low monthly expenditures, smartphone addiction, who use their smartphones for 2-4 hours daily and have a medium GPA (2.01-2.75), 100% belong to sub-dimension 4, which corresponds to the dimension Compulsive Internet Use.

Rule 40:

Attributes: Year of study = 4, Internet plan = 1 (Yes), Marital status = 1 (Single), Average daily smartphone usage frequency = 1 (0-2 hours), GPA = High (2.76 and above)

Result: Sub-dimension = Preference for Online Social Interaction

Confidence: 1 (100%)

Explanation: For single fourth-year students with an internet package, who use their smartphones for 0-2 hours daily and have a high GPA (2.76 and above), 100% belong to sub-dimension 1, which corresponds to the dimension Preference for Online Social Interaction.

Rule 43:

Attributes: Internet plan = 1 (Yes), Monthly average expenditure = 1 (TRY 1 to TRY 5000), Self-reported addiction = 4 (smartphone), Average daily smartphone usage frequency = 2 (2-4 hours), GPA = Mid (2.01-2.75)

Result: Sub-dimension = Compulsive Internet Use

Confidence: 1 (100%)

Explanation: For individuals with an internet package, low monthly expenditures, smartphone addiction, who use their smartphones for 2-4 hours daily and have a medium GPA (2.01-2.75), 100% belong to sub-dimension 4, which corresponds to the dimension Compulsive Internet Use.

Rule 44:

Attributes: Gender = 2 (Male), Age = 19-22, Year of study = 2, Marital status = 1 (Single), Primary reason for smartphone use = 1 (Social media), Average daily smartphone usage frequency = 2 (2-4 hours)

Result: Sub-dimension = Preference for Online Social Interaction

Confidence: 1 (100%)

Explanation: For single males aged 19-22 in their second year, who use their smartphones primarily for social media for 2-4 hours daily, 100% belong to sub-dimension 1, which corresponds to the dimension Preference for Online Social Interaction.

Rule 45:

Attributes: Program enrolled in = 4 (Political Science and Public Administration), Self-reported addiction = 2 (None), Average daily smartphone usage frequency = 3 (4-6 hours)

Result: Sub-dimension = Cognitive Preoccupation

Confidence: 1 (100%)

Explanation: For students in the Political Science and Public Administration department with no existing addiction who use their smartphones for more than 3 hours daily, 100% belong to sub-dimension 3, which corresponds to the dimension Cognitive Preoccupation.

Rule 46:

Attributes: Program enrolled in = 4 (Political Science and Public Administration), Internet plan = 1 (Yes), Self-reported addiction = 2 (smoking), Average daily smartphone usage frequency = 3 (4-6 hours)

Result: Sub-dimension = Cognitive Preoccupation

Confidence: 1 (100%)

Explanation: For students in the Political Science and Public Administration department with an internet package, smoking addiction, and who use their smartphones for 4-6 hours daily, 100% belong to sub-dimension 3, which corresponds to the dimension Cognitive Preoccupation.

Rule 47:

Attributes: Program enrolled in = 8 (Industrial Engineering), Year of study = 3, Monthly average expenditure = 1 (TRY 1 to TRY 5000), Primary reason for smartphone use = 3 (Accessing information)

Result: Sub-dimension = Mood Regulation

Confidence: 1 (100%)

Explanation: For third-year students in the Management Information Systems department with low monthly expenditures who use their smartphones primarily for academic purposes, 100% belong to sub-dimension 2, which corresponds to the dimension Mood Regulation.

These interpretations reflect a variety of combinations of attributes leading to specific sub-dimensions, demonstrating a high level of certainty (100%) in their predictions.

Rule 48:

Attributes: Program enrolled in = 4 (Political Science and Public Administration), Internet plan = 1 (Yes), Monthly average expenditure = 1 (TRY 1 to TRY 5000), Self-reported addiction = 2 (smoking), Average daily smartphone usage frequency = 3 (4-6 hours)

Result: Sub-dimension = Cognitive Preoccupation

Confidence: 1 (100%)

Explanation: For students in the Political Science and Public Administration department who have an internet package, low monthly expenditures, an existing smoking addiction, and use their smartphones for an average of 4-6 hours daily, 100% belong to Sub-dimension 3, which corresponds to the dimension Cognitive Preoccupation.

Rule 50:

Attributes: Program enrolled in = 4 (Political Science and Public Administration), Internet plan = 1 (Yes), Marital status = 1 (Single), Monthly average expenditure =1 (TRY 1 to TRY 5000), Self-reported addiction = 2 (smoking), Average daily smartphone usage frequency = 3 (4-6 hours)

Result: Sub-dimension = Cognitive Preoccupation

Confidence: 1 (100%)

Explanation: For students in the Political Science and Public Administration department who have an internet package, are single, have low monthly expenditures, an existing smoking addiction, and use their smartphones for an average of 4-6 hours daily, 100% belong to Sub-dimension 3, which corresponds to the dimension Cognitive Preoccupation.

Rule 54:

Attributes: Year of study = 3, Monthly average income = 1 (TRY 1 to TRY 5000), Monthly average expenditure = 1 (TRY 1 to TRY 5000), Self-reported addiction = 4 (smartphone), Primary reason for smartphone use = 1 (Social media), GPA = Mid (2.01-2.75)

Result: Sub-dimension = Compulsive Internet Use

Confidence: 1 (100%)

Explanation: For third-year students with low monthly income and expenditures, smartphone addiction, using their smartphones primarily for social media purposes, and a medium GPA (2.01-2.75), 100% belong to Sub-dimension 4, which corresponds to the dimension Compulsive Internet Use.

Rule 56:

Attributes: Gender = 1 (Female), Age = 23-32, Program enrolled in = 1 (Management Information Systems), Year of study = 4, Internet plan = 1 (Yes), Self-reported addiction = 1 (None), Average daily smartphone usage frequency = 3 (4-6 hours)

Result: Sub-dimension = Preference for Online Social Interaction

Confidence: 1 (100%)

Explanation: For female students aged 23-32, studying in the Management Information Systems department, in their fourth year, with an internet package, no existing addiction, and using their smartphones for an average of 4-6 hours daily, 100% belong to Sub-dimension 1, which corresponds to the dimension Preference for Online.

Rule 58:

Attributes: Age = 23-32, Program enrolled in = 2 (International Trade and Finance), Internet plan = 1 (Yes), Marital status=1 (Single), Monthly average income = 1 (TRY 1 to TRY 5000), Monthly average expenditure=1 (TRY 1 to TRY 5000), GPA = High (2.76 and above)

Result: Sub-dimension = Mood Regulation

Confidence: 0.9 (90%)

Explanation: For individuals aged 23-32 who are enrolled in the International Trade and Finance program, possess an internet plan, are single, have low monthly income and expenditures, and maintain a high GPA (2.76 and above), 90% belong to the Mood Regulation sub-dimension group..

These interpretations reflect various combinations of attributes leading to specific sub-dimensions, demonstrating a high level of certainty (100% for most rules) in their predictions.

To examine the relationship between problematic internet use and students' GPAs, along with other sociodemographic and behavioral variables, both parametric and non-parametric statistical hypothesis testing methods were utilized. The Pearson correlation analysis was conducted to determine the association between university students' GPA and their scores on the problematic internet use scale. The results are presented in Table 3.

Table 3. Correlations Between Variables

	Problematic Internet Use	Academic Performance
Problematic Internet Use	1	0.47
Academic Performance	0.47	1

N = 217

The correlation coefficient was found to be $r = 0.46$, $p = .490$. This indicates a weak positive relationship between the two variables, suggesting that there is no significant association between academic performance and problematic internet use among the sample of students. This finding contrasts with existing literature, which predominantly highlights a significant relationship between students' GPA and a lower risk of problematic internet use (Houston and Foubert, 2024; Saquib et al., 2022).

Table 4 presents the results of the independent samples t-tests and a one-way ANOVA examining the relationships between students' GPIUS2 mean scores and various sociodemographic and behavioral variables (gender, year of study, self-reported addiction, program enrolled in, self-reported daily smartphone usage, primary reason for smartphone use, monthly average income and monthly average expenditure) in the study.

Table 4. Respondents' Sociodemographic and Behavioral Characteristics and Problematic Internet Use

Variable	*p*-value	Statistical test
Gender	.592	Independent-samples t-test
Year of study	.349	One-Way ANOVA test
Program enrolled in	.026*	Kruskal-Wallis test
Marital status	.022*	Mann-Whitney U test
Self-reported daily smartphone usage	.000*	One-Way ANOVA test
Primary reason for smartphone use	.000*	Kruskal-Wallis test
Self-reported addiction	.000*	Kruskal-Wallis test
Monthly average income	.302	Kruskal-Wallis test
Monthly average expenditure	.901	Kruskal-Wallis test

N = 217; *P value is significant at .05 level.

Levene's test for equality of variances showed no significant evidence of variance heterogeneity across the groups ($F(1, 213) = .65$, $p = .799$).The independent-samples t-test results indicate that there is no significant difference in GPIUS2 mean scores between females ($M = 4.01$, $SD = 1.45$) and males ($M = 3.90$, $SD = 1.45$) ($t(215) = .537$, $p = .592$). This finding contradicts with literature suggesting that problematic Internet use is generally more prevalent among males (Cao et al., 2011; Kuss et al., 2014; Özgür et al., 2014). However, some studies present contradictory findings, showing no statistically significant relationship by gender (Saquib et al., 2022).

To compare students' problematic internet use scores across different years of study, a one-way ANOVA test was conducted. The one-way ANOVA results indicate that there is no significant difference in the mean GPIUS2 scores across the four years. The F-statistic of 1.103 and p-value of 0.349 suggest that the null hypothesis of equal means cannot be rejected. The mean scores for the groups were as follows: Year 1 (M = 3.92, SD = 1.34), Year 2 (M = 3.89, SD = 1.43), Year 3 (M = 3.78, SD = 1.51), and Year 4 (M = 4.27, SD = 1.48). Contrary to these findings, the literature presents opposing evidence; for instance, Haque et al. (2016) reported statistically significant differences in internet addiction according to students' year of study, with Year 1 exhibiting the highest mean scores.

The Kruskal-Wallis test revealed a significant difference in GPIUS2 mean ranks across the different programs ($\chi^2(7) = 15.948$, $p = .026$). Pairwise comparisons using Dunn's test identified significant differences between Business Administration and Translation and Interpreting (p = .019), Business Administration and International Relations (p = .003), and Management Information Systems and Translation and Interpreting (p = .017), Management Information Systems and International Relations (p = .002), Industrial Engineering and International Relations (p = .020), Political Science and Public Administration and International Relations (p = .017).

The Mann-Whitney U test was conducted to compare the problematic internet use mean scores between single and married students. The results showed a significant difference between the two groups (U = 592.500, Z = -2.282, p = .022). Specifically, single students had significantly higher GPIUS2 mean scores compared to those who are married. This suggests that there is a notable difference in the GPIUS2 mean scores based on marital status. These results align with previous studies, which have also found a significant association between being single and increased problematic internet use (Alqarni et al., 2024; Özgür et al., 2014; Poorolajal et al., 2019). However, Haque et al. (2016) found no significant difference in internet addiction scores based on marital status.

Based on the ANOVA results, there is a significant difference between the means of the groups ($F(3, 213) = 6.833$, p = .000). This indicates that the duration of exposure to smartphone has a significant effect on the mean problematic internet use scores. Levene's test of homogeneity of variances revealed that the variances of the groups are not significantly different (p = .499), which is a necessary assumption for the ANOVA test. The Bonferroni post hoc test results indicate that there are significant differences between the groups. Specifically, significant differences were found between the "0-2 hours" group (M = 3.38, SD = 1.34) and the "4-6 hours" (M = 4.22, SD = 1.51) (p = .016) and "More than 6 hours" (M = 4.80, SD = 1.38) (p = .000) groups, as well as between the "2-4 hours" group (M = 3.77, SD = 1.31) and the "More than 6 hours" group (p = .007). Excessive time spent online (Bergmark et al., 2011) and excessive time spent on social media (Brino et al., 2022) constitute risk factors for problematic internet use. Excessive and compulsive smartphone use can have a significant detrimental impact on the mental health and academic performance of university students (Hashemi et al., 2024). Excessive smartphone use may lead to distractions during study periods and reduce the time allocated to academic activities. Higher levels of phone and social media use while studying correlate with more severe negative effects on learning, including lower grades, diminished academic achievement, reduced academic focus, and increased procrastination (Kutluay and Karaca, 2024; Sunday et al., 2021).

Based on the Kruskal-Wallis test results, the problematic internet use variable exhibits significant differences among different purposes of smartphone usage. The Chi-Square value was 24.148 ($df = 4$; $p = .000$). These findings indicate that the mean ranks of problematic internet use vary significantly across the specified usage purposes. The Kruskal-Wallis test pairwise comparison results indicate that there are significant differences in the sample mean ranks of the purposes of use. Specifically, the purpose of "making calls and sending texts" has significantly lower ranks compared to "social media" ($p = .000$) and "entertainment and photography," ($p = .033$). Additionally, "accessing information" shows a significantly lower rank than "social media" ($p = .031$). Various studies have highlighted that excessive time spent on social media significantly increases problematic internet use (Baltacı and Ersoz, 2022; Tekinarslan and Gürer, 2011).

Given the disproportionate difference in the number of participants across subgroups, a Kruskal-Wallis test was conducted to assess whether there was a significant difference based on the participants' self-reported addiction mean ranks. The Kruskal-Wallis test results indicate that there is a significant difference in problematic internet use mean scores among the different self-reported addiction groups ($p = .000$). The Chi-Square value of 38.403 is significant at a p-value of .000. The test revealed a significant difference in problematic internet use mean scores between the addiction groups. Respondents without any addiction ($n = 120$; Mean rank = 92.67) had significantly lower problematic internet use scores compared to those with smartphone addiction ($n = 36$; Mean rank = 165.68) ($p = .000$). Additionally, a significant difference was observed between individuals with smoking addiction ($n = 57$; Mean rank = 105.66) and those with smartphone addiction ($n = 36$) ($p = .000$), with smartphone addiction showing the highest mean rank among all addiction types, with a mean rank of 164.88. The results suggest that problematic internet use is particularly sensitive to smartphone addiction; students who do not self-report addiction are significantly less likely to experience problematic internet use. A similar finding was highlighted in the study by Çiçek et al. (2023), which found that respondents who spend five hours or more daily on the internet and primarily use it for virtual chatting are more likely to experience problematic internet use.

The Kruskal-Wallis test was conducted to examine the relationship between problematic internet use and monthly average income. The test did not reveal statistically significant differences among the income groups (Chi-Square = 2.391, *df* = 2, *p*. = .302). The mean ranks for each group were as follows: TRY 1 to TRY 5000 (111.33), TRY 5,001 to TRY 10,000 (88.61), and TRY 10001 or more (97.64). Similarly, the association between problematic internet use and monthly average expenditure was examined using the Kruskal-Wallis test, which revealed no significant differences among the groups (Chi-Square = .208, *df* = 2, *p* = .901). The mean ranks for each group were as follows: TRY 1 to TRY 5,000 (109.47), TRY 5,001 to TRY 10,000 (104.00), and TRY 10,001 or more (94.00). Although the current study did not find a statistically significant relationship between these variables, previous research by Ak et al. (2013), Alqarni et al. (2024) and Cao et al. (2011) has identified a link between higher family income and an increased risk of problematic internet use.

Overall, statistical analysis revealed that students' problematic internet use does not vary according to their academic performance, gender, year of study, monthly average income or monthly average expenditure. However, it does differ based on their academic program, marital status, daily smartphone usage, primary reason for smartphone use, and self-reported addiction. Consequently, the central hypothesis of the study, which posits that "problematic internet use among university students varies based on their sociodemographic and behavioral characteristics, as well as their academic performance," is supported.

4. Conclusions and Recommendations

The primary objective of this study is to examine the relationship between university students' internet usage habits and the impact of their sociodemographic and behavioral characteristics, as well as academic performance, on problematic internet use. To achieve this, two distinct methods from different fields were employed: (1) the Apriori algorithm and (2) statistical hypothesis testing.

The results obtained through the association rules reveal the likelihood of problematic internet usage in students with different sociodemographic and internet usage characteristics. For instance, it was found that 100% of male students studying in the International Trade and Finance department with a smoking addiction are in the Mood Regulation dimension (Rule 1). Similarly, second-year students who use their smartphones for an average of 4-6 hours daily and have high GPA also fall into the Mood Regulation dimension (Rule 9). The results from data mining indicate that Mood Regulation is the most prevalent sub-scale of problematic internet use among the sample. This finding is particularly important for understanding students' behavioral patterns, as Caplan (2002) identified mood regulation as a significant cognitive predictor of negative outcomes associated with internet use. In other words, mood regulation primarily involves individuals' use of the internet to modify their emotional state and mood (Caplan, 2002, 2010). Therefore, further studies may be necessary to determine whether university students primarily use the internet as a means to mitigate their negative emotions related to self-presentation in interpersonal situations.

Each of these rules indicates which dimensions individuals with specific demographic and usage characteristics fall into and explains how these dimensions are related to problematic internet usage. For example, it was found that 100% of male students studying Translation and Interpreting who use their smartphones for calling and messaging purposes fall into the Negative Outcomes dimension (Rules 24, 25, 27). Caplan (2002) suggests that this dimension encompasses issues primarily related to personal, social, and professional problems arising from an individual's internet use.

The study also highlighted significant associations between respondents' sociodemographic and behavioral characteristics and their problematic internet use. Being single and having smartphone addiction appear to be risk factors for problematic internet use. Students without addiction had the lowest problematic internet use scores among all subgroups. Excessive time spent on social media was identified as another risk factor for problematic internet use. The results also showed that students who spend more time on their smartphones are more likely to engage in problematic internet use. Students who use their smartphones for more than six hours in a single day have the highest mean of problematic internet use. This information could contribute to the development of preventive strategies by universities and healthcare providers. For instance, educational programs and counseling services could be offered to reduce the negative effects of internet usage, considering specific demographic groups and usage habits.

One strength of this study, which could inform future research, should be noted. Statistical analyses used in such studies provide a robust framework for examining relationships between variables, allowing researchers to test hypotheses and draw conclusions based on data. However, especially when large datasets are available, it may be possible for researchers to apply data mining techniques as well, as it would help them discover hidden patterns and relationships. All in all, the concurrent use of both techniques would enable a more in-depth understanding of the topic under investigation within a target population.

In conclusion, this study offers valuable insights into the potential for problematic internet use among university students. The findings from both analysis methods show significant overlap, offering a crucial foundation for future research aimed at understanding and, ultimately helping professionals mitigate the social and psychological impacts of problematic internet use.

Authors' Contributions

All authors contributed equally to the study.

Statement of Conflicts of Interest

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The authors declare that this study complies with Research and Publication Ethics.

References

Agrawal, R., and Srikant, R. (1994). Fast Algorithms for Mining Association Rules. In *Proceedings of the 20th International Conference on Very Large Data Bases (VLDB)*, 487-499.

Ak, S., Koruklu, N., and Yılmaz, Y. (2013). A study on Turkish adolescent's Internet use: Possible predictors of Internet addiction. *Cyberpsychology, behavior and social networking*, 16(3), 205–209. https://doi.org/10.1089/cyber.2012.0255

Alqarni, A. M., Boubshait, L. A., Alnufaily, D. A., Alalwan, S. J., Fardan, H. R. A., Alabdulmhsin, M. F., Alotaibi, M. A., and Boubshait, N. A. (2024). Prevalence of internet addiction and its association with psychological disorders among medical students in Saudi Arabia. *Psychology Research and Behavior Management*, 17, 2747-2755.

Baloğlu, M., Şahin, R., and Arpaci, I. (2017). A review of recent research in problematic internet use: gender and cultural differences. *Current Opinion in Psychology*, 36, 124-129. https://doi.org/10.1016/j.copsyc.2020.05.008

Baltacı, S., and Ersoz, A. R. (2022). Social media engagement, fear of missing out and problematic internet use in secondary school children. *International Online Journal of Educational Sciences*, 14(1), 197-210.

Bergmark, K. H., Bergmark, A., and Findahl, O. (2011). Extensive internet involvement--addiction or emerging lifestyle?. *International Journal of Environmental Research and Public Health*, 8(12), 4488–4501. https://doi.org/10.3390/ijerph8124488

Bhardwaj, A., Tiwari, A., and Tiwari, V. (2018a). Association rule mining for medical image diagnosis. *International Journal of Information Technology*, 10(2), 153-157.

Bhardwaj, A., Tiwari, A., and Agrawal, S. (2018b). Mining association rules from medical data using Apriori algorithm. *International Journal of Computer Applications*, 180(6), 28-33.

Brino, K. A. S., Derouin, A. L., and Silva, S. G. (2022). Problematic internet use in adolescents and implementation of a social media hygiene protocol. *Journal of Pediatric Nursing*, 63, 84-89. https://doi.org/10.1016/j.pedn.2021.10.011

Cao, H., Sun, Y., Wan, Y., Hao, J., and Tao, F. (2011). Problematic Internet use in Chinese adolescents and its relation to psychosomatic symptoms and life satisfaction. *BMC Public Health*, 11. https://doi.org/10.1186/1471-2458-11-802

Caplan, S. E. (2002). Problematic Internet use and psychosocial well-being: Development of a theory-based cognitive-behavioral measure. *Computers in Human Behavior*, 18(5), 533–575. https://doi.org/10.1016/S0747-5632(02)00004-3

Caplan, S. E. (2010). Theory and measurement of generalized problematic Internet use: A two-step approach. *Computers in Human Behavior*, 26(5), 1089-1097.

Chen, Y., Liu, Z., and Wu, Q. (2018). Applying Apriori Algorithm to Analyze Student Interaction Data in E-Learning Platforms. *International Journal of Learning Technology*, 13(4), 321-338.

Çiçek, E., Uçar, M. T., and Öztürk, M. (2023). Risk factors associated with problematic Internet use in high school students: A nested case–control study. *Addicta: The Turkish Journal on Addictions*, 10(2), 115-126

Das, A., Jana, S., Ganguly, P., and Chakraborty, N. (2021). Application of association rule: Apriori algorithm in E-Commerce. In *2021 Innovations in Energy Management and Renewable Resources (52042)* (pp. 1-7). IEEE. https://doi.org/10.1109/IEMRE52042.2021.9386737

Derbyshire, K. L., Lust, K. A., Schreiber, L. R., Odlaug, B. L., Christenson, G. A., Golden, D. J., and Grant, J. E. (2013). Problematic Internet use and associated risks in a college sample. *Comprehensive Pychiatry*, 54(5), 415–422. https://doi.org/10.1016/j.comppsych.2012.11.003

Fatehi, F., Monajemi, A., Sadeghi, A., Mojtahedzadeh, R., and Mirzazadeh, A. (2016). Quality of life in medical students with internet addiction. *Acta Medica Iranica*, 54(10), 662-666.

Han, J., and Kamber, M. (2001). *Data mining: Concepts and techniques*. Morgan Kaufinann.

Haque, M., Rahman, N. A. A., Majumder, M. A. A., Haque, S. Z., Kamal, Z. M., Islam, Z., Haque, A. E., Rahman, N. I. A., and Alattraqchi, A. G. (2016). Internet use and addiction among medical students of Universiti Sultan Zainal Abidin, Malaysia. *Psychology Research and Behavior Management*, 9, 297-307.

Hashemi, A., Noori, A. Q., Orfan, S. N., Akramy, S. A., and Mohd Rameli, M. R. (2024). Undergraduate students' perception of smartphone addiction and its impact on themselves and their academic performance: a case study. *Cogent Education*, 11(1). https://doi.org/10.1080/2331186X.2024.2340845

Houston, M. L., and Foubert, J. (2024). The relationship between internet addiction test scores and academic achievement. *Growth: The Journal of the Association for Christians in Student Development*, 23(23)

Keleş, A. E., and Kaya, M. (2014). Duvar inşa edilmesinde verimliliği etkileyen faktörlerin Apriori veri madenciliği yöntemi kullanılarak analizi. *Akademik Bilişim Konferansı, AB2014 Bildiriler Kitapçığı*, 831-836.

Kutluay, E., and Karaca, F. (2024). A model proposal explaining the influence of smartphone addiction related factors on high school students' academic success. *Education and Information Technologies*. https://doi.org/10.1007/s10639-024-12947-x

Liu, B., Hsu, W., and Ma, Y. (1998). Integrating classification and association rule mining, *Proc. Fourth Int'l Conf. Knowledge Discovery and Data Mining (KDD '98)*, 80–86.

Liu, Y., Wang, Q., and Shi, X. (2019a). An Apriori-based algorithm for mining association rules in education data. *Journal of Educational Technology Development and Exchange*, 12(1), 1-13.

Liu, Y., Li, H., and Zhao, J. (2019b). Application of Apriori algorithm in analyzing learning behaviors and academic performance. *Journal of Educational Technology Development and Exchange*, 12(2), 45-60.

Mrayyan, M. T., Al-Rawashdeh, S., Khait, A. A., and Rababa, M. (2022). Differences in Cyberchondria, Internet Addiction, Anxiety Sensitivity, Health Anxiety, and Coronavirus Anxiety Among Students: A Web-Based Comparative Survey. *Electronic Journal of General Medicine*, 19(3), 1-8. https://doi.org/10.29333/ejgm/11876

Özgür, H., Demiralay, T., and Demiralay, İ. (2014). Exploration of problematic Internet use and loneliness among distance education students. *Turkish Online Journal of Distance Education*, 15(2), 75-90.

Özparlak, A., Karakaya, D., Önder, A., and Günbayı, İ. (2023). Problematic internet use in adolescents: A phenomenological study. *Journal of psychiatric and mental health nursing*, 30(4), 731–742. https://doi.org/10.1111/jpm.12900

Poorolajal, J., Ahmadpoor, J., Mohammadi, Y., Soltanian, A. R., Asghari, S. Z., and Mazloumi, E. (2019). Prevalence of problematic internet use disorder and associated risk factors and complications among Iranian university students: a national survey. *Health Promotion Perspectives*, 9(3), 207.

Rollo, S., Venuleo, C., Ferrante, L., and De Luca Picione, R. (2023). What Adolescents Have to Say about Problematic Internet Use: A Qualitative Study Based on Focus Groups. *International Jurnal of Environmental Research and Public Health*, 20(21), 7013. https://doi.org/10.3390/ijerph20217013

Sanchez Vega, E., Cantero-Téllez, R., and Rodríguez-Martínez, M. del C. (2016). Internet addiction in future teachers. A case study with university students. *Innoeduca. International Journal of Technology and Educational Innovation*, 2(1), 46–53. https://doi.org/10.20548/innoeduca.2016.v2i1.1063

Saquib, J., Saquib, N., Carras, M. C., AlSalhi, A., Labrique, A. B., Rajab, A. M., Al Jundi, S., and Almazrou, A. (2022). Individual-level correlates of problematic internet use among adolescents: A nationally representative study in Saudi Arabia. *Psychiatry Research Communications*, 2(4). https://doi.org/10.1016/j.psycom.2022.100078

Sunday, O. J., Adesope, O. O., and Maarhuis, P. L. (2021). The effects of smartphone addiction on learning: A meta-analysis. *Computers in Human Behavior Reports*, 4. https://doi.org/10.1016/j.chbr.2021.100114

Tekinarslan, E., and Gürer, M. D. (2011). Problematic Internet use among Turkish university students: A multidimensional investigation based on demographics and Internet activities. *International Journal of Human Sciences*, 8(1), 1028-1051.

Vigna-Taglianti, F., Brambilla, R., Priotto, B., Angelino, R., Cuomo, G., and Diecidue, R. (2017). Problematic internet use among high school students: Prevalence, associated factors and gender differences. *Psychiatry Research*, 257, 163-171. https://doi.org/10.1016/j.psychres.2017.07.039

Witten, I. H., Frank, E., and Hall, M. A. (2016). *Data mining: Practical machine learning tools and techniques* (4th ed.). Morgan Kaufmann.

Zhang, X., Chen, H., and Wang, L. (2020). Apriori algorithm-based analysis of university students' learning behaviors and academic performance. *Educational Data Mining and Learning Analytics*, 14(3), 85-98.