Machine-Learning Predictive Models For Dependency On Smartphones Based On Risk Factors

Claudia F. Giraldo-Jiménez
Universidad Santiago de Cali
Javier Gaviria-Chavarro
Universidad Santiago de Cali
Alexander Urrutia-Valdés
Universidad Santiago de Cali
José Fernando Bedoya-Pérez
Universidad Santiago de Cali
Milton Orlando Sarria-Paja (milton.sarria00@usc.edu.co)
Universidad Santiago de Cali

Research Article

Keywords: Dependency, Addictive Behavior, Smartphone, Artificial Intelligence.

Posted Date: September 29th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-886633/v1

Abstract

Background: Machine learning techniques allow highly accurate prediction of different tasks by measuring the event probabilities. This research proposes a prediction model for dependency on smartphones based on machine learning techniques.

Methods: We performed an analytical observational study with a retrospective case–control approach; the different classification methods used were decision tree, random forest, logistic regression, and support vector machine. The sample demographic included 1228 students from a private university in Cali. The tests were 1) smartphone dependency assessment and 2) the Nordic musculoskeletal symptoms questionnaire.

Results: It was found that some of the variables related to smartphone dependency are academic curriculum, school, marital status, socioeconomic status, rules, discussions, and discrimination.

Conclusions: The support vector machine model evidences highest prediction precision for smartphone dependency, obtained through the stratified-k-fold cross-validation technique.

Background

Nowadays, the use of smart mobile phones (smartphones) is commonplace in different areas of daily life, such as at work and in education [1]. For instance, smartphones are effective learning tools in educational settings to gain knowledge, although with both positive and negative effects derived from their usage for the young population [2, 3]. There is a significant effect on undergraduate students' academic performance when learning with mobile applications, compared to traditional learning [4]. Case studies show how industrial, educational, commercial, and advertising sectors create their own mobile applications as a means of communication among population groups, work environments, work teams, and demographic patterns [5]. This gives provides the business sector with information toward the development of mobile applications for achieving business objectives, covering new markets, and attracting demand [6].

Smartphones have a repertoire of mobile tools, which altered the consumption dynamics and the way users interact [7]. In particular, consumer and information applications as well as social networks have high demand, and have high influence in individual communication and lifestyle habits [8]. In the last decade, the use of mobile devices (cell phones) in different communities has become widespread, and its lasting effects have been multiplied. Thus, technological improvements generates the need to analyze strategies that guide students in efficient management of technological resources, which strengthens the learning process [9].

The effects of smartphone usage on cognitive abilities for educational, occupational, and social functioning can be classified as negative or positive from their socio-emotional components [10].

Likewise, evidence shows impact on children and young people's mental health and well-being, triggered by exposure times, connectivity and compulsive behavior [11].

The use of mobile devices is an occupational reality [12]. Work and educational environments have implemented smartphone-based tools [13]. Also, an added value of smartphones is its personal use for daily task organization, communication with relatives and entertainment, which increases the ubiquity in daily routines of digital tools[14]. The available tools have three features in their use: accessibility, repetition, and interactivity. These features generate a high level of affinity toward these devices, among which smartphones stand out [15].

Mobile-device dependency is a problem that is established in terms of frequency and excessive use. There is a 38.9% prevalence of excessive use of mobile-devices over all the population in this study, with significant representation in the young population [16]. This habit is negatively associated with inhibition, decision making, memory performance, and sleeping difficulties [17]. Studies show that the simultaneous use of a cell phone during daily activities could represent a greater load for muscle chains, classified as a risk factor in musculoskeletal problems [18].

Different studies on an individual's and adolescents' problems with mobile devices show preferences toward gaming and general applications availability on these platforms [19]. These applications are an integral part of modern life and therefore can create unfavorable dependency [20]. For this reason, it is important to quantify the dependency with objective scales and to incorporate ways of analyzing the effects of excessive and antisocial use of smartphones [21].

Therefore, the excessive use of smartphones has prevalence among student populations, where access to internet, use of big screens, game interaction, and unlimited data were significantly associated with levels of blindness, deafness, and inattentiveness [22].

In this paper, we propose to apply the SDT questionnaire to assess the dependency on mobile devices among the university student community. This questionnaire was validated and linguistically adapted in 2016 for public and private university students, with a reliability for abstinence and tolerance ($\alpha = 0.901$), for abuse and difficulty in controlling the impulse ($\alpha = 0.853$), and for problems caused by excessive use ($\alpha = 0.762$) [23].

Despite sparse existing research about predicting dependency levels on smartphones through machine learning techniques, it is pertinent to apply these techniques due to the computational level acquired lately [24, 25]. It is worth mentioning that there is a significant advance in the use of these tools to solve different research problems, in particular those evaluating the effectiveness of machine learning. However, they have not been widely used to generate predictive models focused on smartphone dependence [26, 27].

This research proposes a prediction model for smartphone dependency among the university student population, based on machine learning techniques related to individual, family, environmental risks,

physical load, device-specific risk factors, and musculoskeletal symptoms.

Methods

This is an analytical observational study, in which a retrospective case-control approach was used.

Participants and procedures

The study was conducted with students from a private university in 2019, within a sample size (N) of 14858 students. The selection-sampling frame consisted of a student list from the 19 undergraduate programs of 4 schools. For the sample calculation, a 95% confidence level and a 5% margin of error are used, resulting in a sample of n = 1247 students. The sampling technique was defined as stratified random. The strata comprised undergraduate programs. The selection of the participants was performed by probability sampling, using the epi-info software. Eighteen individuals were excluded because they met the exclusion criteria, as they used the upper limbs in regular physical activities such as participating in high-impact sports (basketball, volleyball, table tennis and weights in the gym) and repetitive movement in artistic activities (such as painting, embroidery crafts and playing musical instruments such as guitar and *tambora*), whose frequency and intensity could cause information bias, which allowed the control for selection bias. Therefore, the final sample was recalculated for 1228 students (95% CI; 5% error). According to the Levene homogeneity test, the sample was comparable for age, sex, program, semester, and marital status (0.157–0.740). The participants were then assigned to two groups. The case group represented students who showed some level of smartphone dependency, and the control group was represented by those without smartphone dependency.

Participants duly enrolled and who signed the informed consent voluntarily were also considered as inclusion criteria. Those who submitted an incomplete form and those who frequently played sports or artistic endeavors where the use of the upper limbs could significantly cause selection bias, were excluded.

To link the participants, the shortlisted candidates were invited from classrooms. The ones absent were replaced by the next participant on the list who met the inclusion criteria and who was of the same sex. Subsequently, informed consent forms was signed. Data collection was cross-sectional.

Variables considered

The free-to-use **Smartphone Dependency Test** was created by Mariano Chóliz Montañés [28], which was validated and linguistically adapted in 2016 for students receiving both public and private education [29]. This test was used to measure the dependent variable that was the level of independence to Mobile Devices (MD). The test lasted 10 min, and consisted of 22 items on a Likert-type scale, whose scores range from 0 (zero) as the minimum value to 88 as the maximum value and thus determine whether the dependency was absent, low, medium, or high. Musculoskeletal disorder (MSD) was characterized via the **Nordic Questionnaire**, in its Spanish validated version, whose application lasted 7 min. The questionnaire

comprised two levels: a general level that sought to determine the occurrence of musculoskeletal discomfort by anatomical regions, and a specific level that focused on delving into the chronology, frequency, duration, intensity, and impact of the discomfort on their normal activities.

The risk factors were the independent variables. The **Risk Factors Questionnaire** was designed and subjected to internal validation by the researchers through the Delphi method by a group of 6 experts, obtaining a validity of 0.891 according to Chronbach's alpha; its application lasted 7 min. This questionnaire included the variables considered in the theoretical framework about some sociodemographic, interpersonal, and contextual factors related to the device and physical load, with which it was possible to identify the risk factors that occur in the university student population [30].

Analysis

The data were recorded by double entry in Excel. The information from the two databases were compared, and unmatched data were cleaned, performing verification in the primary source.

In the processing and analysis phase, the variables were transformed into categorical type to structure the model construction. The data allocation, which was 1%, was performed using the qualitative variables' mode and the quantitative variables' mean. Once the information was validated, a descriptive exploratory analysis of the different variables was conducted to determine their behavior. Subsequently, a bivariate analysis was performed to determine which of them were included in the model, and selected for statistical significance with a p-value < 0.05.

Figure 1 shows a diagram with the basic blocks that constitute a general-purpose pattern-recognition system. We can identify a feature extraction stage, feature transformation (optional), and finally a classification block. Next, we discuss in detail about the adjustments made in each block to implement our system.

The information processing, debugging, modeling, and validation of data were structured in six stages, which are described in Fig. 2.

Supervised learning techniques

In order to have a clear notation, $x^{(i)}$ is used to denote the input variable, also known as characteristics, with n dimensions. $y^{(i)}$ is used to show the output or target variable that we seek to predict. The pair $(x^{(i)},y^{(i)})$ is a training example. The dataset containing the information from m training examples $\{(x^{(i)},y^{(i)})\}$; $i = 1\ldots m$, is known as a database or training set. Typically, **X** and **Y** are used to show the space representations of the input and output variables, respectively. When a classification problem is approached, the variables in the **Y** space take discrete values, corresponding to the classes or categories defined in the learning problem. For the specific problem addressed in this work, $y \in \{0, 1\}$, where a value y = 0 has been defined to indicate a person with a negative diagnosis, whereas y = 1 indicates a person with a positive diagnosis for smartphones dependency.

To describe the supervised learning problem, we generally consider the problem of estimating a function h: **X**→**Y**, such that given an example of input *x*, h(x) predicts the y value. The function h(x) is also known as the hypothesis function.

Logistic regression

In supervised learning, the logistic regression model uses a logistic function to model a binary variable. This is used to predict the class or event probability. The following hypothesis function is used

$$h_\theta(x) = \frac{1}{1+e^{-\theta^T x}}$$

1

Where θ represents the set of parameters to be adjusted during the training process. Once the parameters of the function have been adjusted, the probability of a class can be calculated as follows [31]:

$$P\langle y=1 \mid x;\theta\rangle = h_\theta(x)$$
$$P\langle y=0 \mid x;\theta\rangle = 1 - h_\theta(x)$$

2

Support vector machine

The support vector machine is a binary classifier which models the decision boundary between two classes as a separating hyperplane. The support vector machine's training process involves finding a separating hyperplane that maximizes the separation between the two classes. The discriminant (or hypothesis) function is given by

$$f(x) = \sum \alpha_j c_j K\left(x, x_j\right) + b$$

3

where c_j are the labels for the training samples. The kernel function denoted by $K(\bullet,\bullet)$ represents the dot product in the feature space. The support vectors x_j, their weights a_j, and the bias term b are determined during training [32].

Decision tree

A decision tree exhibits a flowchart-like tree structure, whereby it splits data hierarchically into subsets, which are then split again into the smaller partitions. The internal nodes of the tree are input patterns (or tests) and the leaf nodes are categories. A decision tree assigns a class to an input pattern by filtering down the pattern through the tests in the tree [33]. See Fig. 3.

Random forest

This is a classifier composed of a collection of tree-structured classifiers. We can denote this collection as $\{h(x,\Theta_k), k = 1,..\}$, where $\{\Theta_k\}$ are independent identically distributed (iid) random vectors. Each classifier votes for the most popular class at input x. For additional details, we refer the interested reader to [34].

System validation:

The assisted diagnosis process using automated systems is an imperfect process. The result obtained from a classification system represents a probability rather than a correct answer with irrefutable certainty. Different diagnostic measures are thus employed to verify and assure that the results are repeatable and to validate the ability of a system to identify the presence or absence of a disease.

In these experiments in particular, random cross-validation is used in its stratified version to guarantee the proportions in each one of the sets [35]. The available data is split into two disjoint subsets, such that 70% of the data is used for training, and the remaining 30% is used as a test set [36].

Each technique described above is evaluated using the validation strategy, i.e., logistic regression, support vector machine, decision tree, and random forest. For assessing the performance of each model, diagnostic measures such as sensitivity, particularity, accuracy, and precision are used. Additionally, the receiver operating characteristic (ROC) curve and its area are included [37, 38].

TP = true positive
TN = true negative
FP = false positive
FN = false negative

Accuracy $= \frac{TP + TN}{TP + TN + FP + FN}$

Specificity $= \frac{TN}{TN + FP}$

Sensitivity $= \frac{TP}{TN + FN}$

Precision $= \frac{TP}{TP + FP}$

Results

Figure 4 shows a pie chart of the response-variable distribution in the dataset and the percentage of the categories, i.e., presence or absence of dependence on the smartphone.

An initial analysis is conducted to identify the variables that may have a greater relationship with the response variable on the collected data. Hence, we performed a chi-square test for categorical variables

and the odds ratio (OR) for dichotomous qualitative variables, bearing in mind that the OR is a measure to express the possibility of occurrence of an important event (dependency). According to this analysis, a relationship of the following variables was found in students with dependency and without dependency on smartphones:

i. Academic program; ii. school; iii. marital status; iv. socioeconomic status; v. Is it possible to express oneself in the family? vi. May the student be discriminated for not having a smartphone? vii. Arguments about spending a lot of time with a smartphone; viii. residence area; ix. the type of access to the network; x. most used space; xi. time of acquisition; xii. average use time per day; xiii. posture you use when interacting with the phone: sitting on the floor, lying on the side, lying on the back; xiv. amount of time with body discomfort; and xv. duration of each episode of wrist discomfort.

In Colombia, there is a socioeconomic stratification system which aims to classify urban populations into different strata with similar economic characteristics. The system classifies areas on a scale from 1 to 6 with 1 as the lowest income area and 6 as the highest.

Table 1 shows the discriminated results for each one of the mentioned variables. In the first column, the risk factors are presented, and in the second column, the variables and their corresponding sub-categories are presented. Columns 3 and 4 show the frequency and percentage of students classified as having dependency (cases) or without dependency (controls), respectively. Finally, in the fifth column, the p-value obtained from the chi-square test is presented, which has as a null hypothesis that the variables do not present any relationship.

Table 1. Qualitative variables: university students with and without smartphone dependency.

The response associated with the identification of musculoskeletal discomforts is also analyzed. In this case, we observe that the body region with the highest risk factor was the wrist with an OR = 1.93, with a 95% confidence range. Furthermore, the neck, shoulder, back, and elbow regions also showed very similar associations OR = 1.42, OR = 1.62, OR = 1.88, and OR = 1.89, respectively. The summary of the results is presented in Table 2.

Risk factors	Variables	Cases	Control	P
Sociodemographic	**Academic program**			0.000
	Administration	42 (66.7)	21(33.3)	
	Bioengineer	36(60.0)	24(40.0)	
	Accountancy	27(42.9)	36(57.1)	
	Law	201(68.1)	94(31.9)	
	Economics	29(46.0)	34(54.0)	
	Nursing	41(59.4)	28(40.6)	
	Finance	21(33.3)	42(66.7)	
	Physiotherapy	44(89.8)	5(10.2)	
	Speech Therapy	29(100.0)	0(0.0)	
	Industrial Engineering	60(100.0)	0(0.0)	
	Electronic Engineering	37(61.7)	23(38.3)	
	Engineering Energy	60(100.0)	0(0.0)	
	System Engineering	60(100.0)	0(0.0)	
	Surgical Instrumentation	21(60.0)	14(40.0)	
	Medicine	47(83.9)	9(16.1)	
	Marketing	31(64.6)	17(35.4)	
	Dentistry	37(90.2)	4(9.8)	
	Psychology	20(74.1)	7(25.9)	
	Respiratory Therapy	20(74.1)	7(25.9)	
	Faculty			0.000
	Health	259(77.8)	74(22.2)	
	Economic Sciences	150(50.0)	150(50.0)	
	Engineering	253(84.3)	47(15.7)	
	Law	201(68.1)	94(31.9)	
	Civil Status			0.021
	Single	737(72.0)	287(28.0)	
	Married	48(66.7)	24(33.3)	

Separated	8(53.3)	7(46.7)	
Divorced	3(100.0)	0(0.0)	
Widowed	1(100.0)	0(0.0)	
Cohabitation	66(58.4)	47(41.6)	
Socioeconomic stratification			0.000
1	60(63.2)	35(36.8)	
2	167(55.5)	134(44.5)	
3	367(74.1)	128(25.9)	
4	159(78.3)	44(21.7)	
5	96(82.8)	20(17.2)	
6	14(77.8)	4(22.2)	

Interpersonal	**Who do you live with?**			0.001
	Both parents	255(67.3)	124(32.7)	
	Mother/father	153(72.2)	59(27.8)	
	Another family member	244(78.5)	67(21.5)	
	Friend	75(72.1)	29(27.9)	
	Partner	75(61.0)	48(39.0)	
	Alone	61(61.6)	38(38.4)	
	Can you be discriminated for not owning a smartphone?			0.000
	No	537((66.5)	270(33.5)	
	A little	139(74.7)	47(25.3)	
	Some	112(81.2)	26(18.8)	
	A lot	61(82.4)	13(17.6)	
	Extremely	14(60.9)	9(39.1)	
	Arguments for spending too much time on the smartphone			0.000
	No	496(65.0)	267(35.0)	
	A little	158(78.6)	43(21.4)	
	Some	110(76.9)	33(23.1)	
	A lot	74(80.4)	18(19.6)	
	Extreme	25(86.2)	4(13.8)	
	Are there any rules for the smartphone use at home?			0.000
	No	243(58.1)	175(41.9)	
	A little	414(74.3)	143(25.7)	
	Some	102(79.1)	27(20.9)	
	A lot	74(82.2)	16(17.8)	
	Extreme	30(88.2)	4(11.8)	
Context sensitive	**Type of Internet connection**			0.000
	Mobile data	432(65.3)	230(34.7)	
	Wifi	422(76.0)	133(24.0)	
	Both	9(81.8)	2(18.2)	

	Places of more smartphone use			0.004
	Home	430(66.3)	219(33.7)	
	University	379(74.3)	131(25.7)	
	Shopping malls	54(78.3)	15(21.7)	
Related to the mobile device	**Time since you acquired your first cell phone**			0.000
	Less than 6 months	42(80.8)	10(19.2)	
	From 6 months to 1 year	250(75.1)	83(24.9)	
	1–3 years	87(60.4)	57(39.6)	
	3–6 years	140(59.6)	95(40.4)	
	More than 6 years	343(74.1)	120(25.9)	
	Average time of use per day			0.000
	Less than an hour	35(61.4)	22(38.6)	
	1–3 hours	173(58.4)	123(41.6)	
	3–6 hours	205(65.9)	106(34.1)	
	More than 6 hours	449(79.8)	114(20.2)	
Physical Load	**Do you use your smartphone sitting on the floor?**			0.001
	Less than an hour	496(66.3)	252(33.7)	
	1–3 hours	339(77.2)	100(22.8)	
	3–6 hours	24(72.7)	9(27.3)	
	More than 6 hours	4(50.0)	4(50.0)	
	Do you use your smartphone lying on one side?			0.000
	Less than an hour	495(64.2)	276(35.8)	
	1–3 hours	311(80.2)	77(19.8)	
	3–6 hours	46(86.8)	7(13.2)	
	More than 6 hours	11(68.8)	5(31.3)	
	Do you use your smartphone lying on your back?			0.000
	Less than an hour	394(63.4)	227(36.6)	
	1–3 hours	371(77.8)	106(22.2)	
	3–6 hours	75(78.1)	21(21.9)	

More than 6 hours	23(67.6)	11(32.4)	
How long have you had any discomfort?			0.000
Less than a month	532(65.8)	277(34.2)	
Between 2 and 3 months	133(79.6)	34(20.4)	
Between 4 and 6 months	81(78.6)	22(21.4)	
Between 7 and 9 months	30(83.3)	6(16.7)	
Between 10 and 12 months	87(77.0)	26(23.0)	
Duration of each wrist episode			0.014
Less than an hour	730(68.8)	331(31.2)	
Between 1 and 24 hours	80(82.5)	17(17.5)	
Between 1 and 7 days	30(85.7)	5(14.3)	
Between 1 and 4 weeks	9(69.2)	4(30.8)	
More than a month	14(63.6)	8(36.4)	

Table 2
Bivariate analysis. Discomfort in university students with and without smartphone dependency.

Significative Variables	Cases n	Controls n	OR (CR95%)
DO YOU EXPERIENCE ANY DISCOMFORT IN			
Neck			
Yes	502	180	1.429 (1.118–1.827)
No	361	185	
Shoulder			
Yes	305	92	1.622 (1.233–2.134)
No	558	273	
Back			
Yes	347	96	1.884 (1.439–2.468
No	516	269	
Elbow			
Yes	163	40	1.892 (1.307–2.739)
No	700	325	
Wrist			
Yes	341	92	1,938 (1,476-2,547)
No	522	273	

The time during which each individual manifested discomfort was analyzed, in an interval of 12 months. The OR values show the results between 1.45 and 1.69; the elbow and shoulder region share the highest value, while the back region has the lowest value. Table 3 shows the results obtained.

Table 3
Bivariate analysis. University students experiencing discomfort in the last 12 months with and without dependency on smartphone.

Significant variables	Cases n	Controls n	OR (CR95%)
DISCOMFORT DURING THE LAST 12 MONTHS			
Neck			
Yes	399	127	1.611 (1.251–2.077)
No	464	238	
Shoulder			
Yes	238	67	1.694 (1.250–2.296)
No	625	298	
Back			
Yes	309	101	1.458 (1.115–1.906)
No	554	264	
Elbow			
Yes	149	40	1.696 (1.168–2.462)
No	714	325	
Wrist			
Yes	580	280	1.607 (1.213–2.129)
No	283	85	

Automated diagnosis system

All the significant variables from the different models performed were included. A total of 31 variables that were related to the dependent variable (dependence on smartphone) were obtained.

Table 4 shows the results for all classifiers evaluated. In Table 4, we are presenting five diagnostic measures: accuracy, specificity, sensitivity, precision, and the area of the ROC curve. Some differences can be observed in the selected metrics. For example, the decision tree has the lowest overall rates, except for specificity. In contrast, it was observed that for the case of logistic regression, random forest, and support vector machine, better sensitivity rates were achieved, but specificity had significantly reduced.

In order to perform a global evaluation for each classifier, the ROC curve was added (Fig. 5). It was effectively observed that the classifier with the lowest performance corresponds to the decision tree. According to the results, except for the decision tree, it was impossible to determine which among the 4 remaining approaches offered the best performance. However, considering the simplicity of the model

and the number of parameters that must be estimated, the classification approach using logistic regression represents a simple system with an acceptable performance for the task at hand.

Table 4
Predictive Performance

Classifier	Accuracy	Sensitivity	Specificity	Precision	AUC
Decision Tree	70.5 ± 2.0	78.9 ± 2.9	50.1 ± 2.7	79.2 ± 0.9	0.645 ± 0.01
Logistic Regression	75.7 ± 1.5	91.1 ± 1.4	38.7 ± 3.4	78.2 ± 1.0	0.712 ± 0.02
Random Forest *n_e = 20*	75.9 ± 1.3	91.4 ± 0.7	38.5 ± 4.7	78.2 ± 1.2	0.722 ± 0.03
SVM poly *C = 1, γ = 5, d = 2*	75.6 ± 1.2	92.5 ± 0.5	34.8 ± 3.9	77.4 ± 1.0	0.726 ± 0.01
SVM rbf *C = 10, γ = 3*	76.2 ± 1.3	92.2 ± 0.9	37.5 ± 3.6	78.1 ± 1.0	0.723 ± 0.01

It is worth adding that a system with high sensitivity leads to situations wherein a dependency can be suspected, but additional evaluations are required to confirm its presence. It is also useful in the early stages of a diagnosis, where the opinion of multiple professionals may be required to reject or confirm the onset of any specific condition.

Discussion

The findings identify that there are four classification models that can yield satisfactory results in predicting smartphone dependency. Likewise, a relationship between smartphone dependent and non-dependent students and multiple risk factors was found, which should motivate establishing high-priority preventive actions among the university students.

In this study, student enrollment to an academic program or faculty showed a significant correlation with the level of smartphone dependency ($p = 0.00$). As a result, it is obtained that 253 (84.3%) students enrolled in the engineering faculty show signs of smartphone dependency. As for the health school, 259 (77.8%) students, 150 (50.0%) students from the economic sciences faculty, and 201 (68.1%) the law school students. Other works accessed do not allow similar comparisons. However, a study conducted at Mackenzie Presbyterian University, in the City of Sao Paulo (Brazil), showed that 124 (48.2%) students from the faculty of humanities, 43 (16.7%) from natural sciences, 7 (2.7%) from applied and formal sciences, and 83 (32.3%) from others [40] have some level of smartphone dependency. The department with the highest proportion showing signs to smartphone dependency was the health school (n = 259; 77.8%), mostly belonging to the medical academic program (n = 47; 83.9%).

Regarding the university students' marital status, it was found that dependent students are 72% single, and there was a statistically significant difference between marital status in relation to smartphone dependency ($p = 0.021$). Ivanova and Gorbaniuk [41] found a similar result. They analyzed the use of the smartphone in 402 university students and found that 91.1% were single, 7.9% married and 1.0% divorced, finding loneliness and not having a partner leads to levels of depression and phubbing due to smartphone use and obsession ($p < 0.01$). Likewise, the study by Zhao and Lam [42, 43] evaluated the use of the smartphone as a means of communication, and they found that the characteristics of being single, cohabiting, separated, or widowed have significant effect on the use of the smartphone to communicate with their family nucleus through instant messaging groups ($p = 0.006$).

Alternatively, Xie and Molassiotis [43] studied a group of 1500 individuals, corresponding 60.5% to married or cohabiting marital status and 39.5% single, establish the relationship of smartphone use with a prevalence of 78.9% over the target population, highlighting the use in youth and young adults. Thus, Jeong and Jeong [44] also evaluated the sociodemographic characteristics and social relationships, including the family, to find deficiencies in the daily activities of 190066 participants, who played games, used the internet, and used smartphones. The results showed that 130531 were married, 26079 were divorced, and 33456 were single, where the characteristics of being divorced and single were significant in having experienced mild to moderate disabilities via the excessive use of smartphones, with a p-value < 0.001.

The socioeconomic stratum in this study had significance ($p = 0.000$), supported by economic theory, where monthly family income is a factor that determines the individual socioeconomic level. Zhao and Lam [42] found that high family income is meaningful in the use of the smartphone to communicate with their family nucleus through instant messaging groups ($p < 0.001$). Income and employment status are determining elements in the individual economic level, in the study by Romero-Rodríguez and Rodríguez-Jiménez [45]. They surveyed 385 university students with permanent use of smartphone, and found that 51.7% were active workers and 48.3% were unemployed. Both work situations showed a relationship in the smartphone frequency use through the social network application ($p = 0.002$). Similarly, Xie and Molassiotis [43] studied a group of 1500 individuals, where 44.8% presented high income, 29.2% medium income and 26% low income, therefore establishing a relationship in the use of the smartphone with a prevalence of 78.9% over the target population.

Freitas & Cols. [16] state in their review that young people with high family income have a greater probability of developing smartphone dependency. Thus, the comparison with previous studies, strengthens the hypothesis where the socioeconomic stratum is significant for assessing the smartphone dependency.

Alternatively, Balogun and Olatunde [46] studied the problems of smartphone use in a population of 1230 young people and young adults, with the distribution of socioeconomic classes in a (27.8%) Class I, (58.2%) Class II, (12.4%) Class III and (1.6%) Class IV. Access to the phone and phone use by the respondents showed a prevalence of 96.7% with positive activation of smartphone functions. It showed

that different social levels have access to unlimited use of the smartphone, but there is no significant difference in the smartphone dependency problem with $p = 0.91$.

The possibility of being discriminated for not having a cell phone was shown to have a significant difference ($p = 0.000$) in students with a smartphone dependency, which motivates us to continue investigating in depth the causes that lead to its acquisition. Likewise, in the research by Vaterlaus and Martin [47] performed with 686 teenagers, it was found that those who did not have a smartphone to meet their communication needs were more susceptible to bullying and not having it became socially unacceptable, obtaining a significant difference ($p < 0.01$).

Regarding the argument in the family due to spending a lot of time with the smartphone, the results showed that 496 (65.0%) participants report not having any type of discussion. Thus, in a sample of 351 undergraduate students from the Department of Health Sciences of the public university in southern California, it was found that close to half the sample (48%) acknowledged having experienced between 1 and 3 situations of domestic adversity and a percentage lower than 10% acknowledged having experienced more than four situations of domestic adversity. By relating domestic adversities to the risk of presenting problematic/addictive smartphone use (PSU), students who reported one to three adversities (4.7%) at home were approximately 2 times more likely to have PSU (OR 2.11, 95% CR 1.13–3.93); for students who reported adversity at home four or more times (9.4%), they were four times more likely to have PSU (OR: 4.35, 95% CR: 1.86–7.84) compared to students who did not present stressful conditions [48].

In relation to the type of internet access, a significant difference was found between those who do access the internet by paying for data packages ($p=0.000$). Similar results were found by Balogun and Olatunde [46], who studied the problems of smartphone use among the young population; they found that the data used for the phones are mainly financed by the parents. These phones are used to surf the internet, make calls, and send text messages. The result showed that having a data plan is a predictor for smartphone use problems with an OR of 1.47 and 95% CR 1.05–2.05.

The environments or spaces in which university students use the smartphone present a level of statistical significance with dependence on it ($p = 0.004$), and the main environment for dependent students is their home (66.3%). Tangmunkongvorakul and Kihara [49] analyzed the smartphone use of 7694 students in educational spaces in two populations. The total sample was divided in two groups, i.e., group 1: 1109 students from Thailand and group 2: 6585 students from Japan. According to the analysis, the prevalence of smartphone addiction was 35.9% for group 1, and a student from this group was was almost 2.7 times more likely to be addicted than a student from group 2. This result was associated with the use of social networks and communication needs. On the contrary, Merma-Molina and Álvarez-Herrero [50] determined that addiction to mobile devices has a significant difference with their use in the educational environment (Chi squared χ^2: 192.026, $p<0.001$). While Cha and Seo [51] in their study establish that young people after returning from their educational spaces in the afternoon were 2.65 times (CR 1.07–6.56) more likely to generate smartphone dependency than those who were busy with

their educational environments. Therefore, the greater the number of hours of use, the greater the probability of developing dependency.

In relation to the first cell phone acquisition, it was found that 74.1% (n = 343) of the students with a smartphone dependency acquired it for the first time more than 6 years ago. A similar study in 249 participants found that 42.6% of the students (n=106) presented significant results between the time of acquisition of the smartphone and the addiction to the smartphone (p = 0.027) [52].

In this study, the participants who present addiction to the smartphone in relation to the time of use per day was 79.8% (n = 449), and they use it for periods greater than 6 hours. In a study conducted with students of medicine, dentistry, pharmacy, nursing, and rehabilitation programs at the University of Jordan in the Hashemite Kingdom of Jordan [53], a significant difference was found (p < 0.001) regarding the use of mobile phones when analyzing the duration of the use time for the students of the different programs. The students of the dentistry program use the smartphone in an average of 9.8 ± 7.1 hours per day, whereas for the students of medicine (p < 0.001; mean = 5.9 ± 4.2 hours/day), for nursing program students (p = 0.013, mean = 5.8 ± 5.6 hours/day), and for the pharmacy students (p = 0.001, mean = 6.3 ± 3.5 hours/day).

Likewise, Freitas & Cols. in their literature review found that teenagers who use the device 5–6 hours a day are 10.78 times more likely to become dependent. While those who use the device 3–4 hours a day have 5.79 times the chance [16]. Similarly, Thapa and Rima [54] studied the prevalence of smartphone dependency for 405 undergraduate students. The prevalence was found to be 21.8%, and according to the authors, this dependency was highly related to variables such as time spent on mobile, number of calls per day, years of ownership of a mobile phone, as well as money spent on recharge per month. As regards the predominant posture for using a smartphone, a significant difference was found between the sitting position (sitting position: 66.3%; n = 496) during smaller periods of time (less than an hour; p = 0.001). The study by Al-Hadidi [53] reported that the preference for using the smartphone while seated in women is 68.2% and in men is 31.8%.

The university students who present smartphone dependency reported having discomfort or musculoskeletal symptoms for less than 1 month (n = 532, 65.8%), resulting in this variable with statistical significance (p = 0.00) and a significant association with the highest risk factor in the wrist (OR = 1.93; 95% CR 1.47–2.54). In this regard, in a cross-sectional study conducted in Turkey with 249 participants, the researchers reported that the highest prevalence of musculoskeletal pain was in the upper back (70.3%), neck (65.9%) and wrists/hands (68.7%). They were correlated with the duration of smartphone use (p = 0.001) and the prevalence of musculoskeletal pain in the neck (p = 0.001), wrists (p = 0.001) and shoulders (p = 0.025), where there was a significant association with the prevalence of musculoskeletal pain in the neck (OR = 1.08; 95% CR, 0.98–1.10) and wrists (OR, 1.07; 95% CR, 0.97–1.09) [51]. The results shown are similar to this work.

Likewise, another cross-sectional study conducted in Saudi Arabia with 387 medical students reported a significant correlation between smartphone addiction and high scores for wrist and thumb pain (p =

0.036); they concluded that intensive use of these devices can cause subclinical effects in the human hand [54].

As regards the neck, this work found that those students with a smartphone dependency have approximately 1.42 times more risk of suffering neck pain than those without. In this regard, a descriptive study conducted in Iran with 1602 office workers found a 30.1% prevalence of neck pain among those who make excessive use of smartphones. Results from multiple logistic regression models revealed that those with excessive smartphone use are approximately 6 times more likely to have neck pain (95% CR 4.44–8.09, $p < 0.001$) [55]. Similarly, a study conducted with 1691 teenagers in Singapore (51% girls, 10–19 years) reported prospective associations between the use of reference smartphones and neck/shoulder follow-up symptoms (OR = 1.61 (95% CI: 1.06–2.44)) and the those in the lower back (OR = 1.86 (95% CI: 1.10–3.14)) [56].

Conclusions

The support vector machine model presents the highest prediction precision for smartphone dependency, obtained through the stratified-k-fold cross-validation technique.

Given the 91% model sensitivity, it is not specific for predicting non-dependency on the smartphone.

The presence and duration of musculoskeletal discomfort in the last 12 months contributes to the prediction of smartphone dependency.

From the variables used in the model, it is found that the sociodemographic characteristics determine a level of smartphone dependency. Despite the above, the age and gender variables must be ruled out.

Due to the large number of variables used in this study and its multiple factors for smartphone dependency, the machine learning model is the most appropriate.

This work was cross-sectional in data collection; thus, it is recommended that future studies be longitudinal. The inclusion and analysis of variables related to academic performance, mental health, and sleep disorders are suggested for future studies.

Abbreviations

MD: Mobile Device; SDT: Smartphone Dependency Test; OR: Odds Ratio; MSD: Musculoskeletal Disorder; ROC: Receiver Operating Characteristic; SVM: Support Vector Machine; PSU: Problematic/Addictive Smartphone Use

Declarations

Author’s contributions

All authors contributed to the writing and design of the study.

CFG contributed with data acquisition and manuscript writing.

JGC and MOSP contributed with data analysis and manuscript writing.

AUV and JFBP participated in the manuscript writing. All authors read and approved the final manuscript.

Funding

This research has been funded by Universidad Santiago de Cali, Dirección General de Investigaciones under call No. 01-2021.

Materials and data availability

Datasets analyzed during the current research are available upon reasonable request to the corresponding author.

Ethics approval and consent of participants

The study followed the principles of the Helsinki Declaration, guaranteeing confidentiality by coding and signing the informed consent prior to participation.

Regarding data collection, the protocol of this study was doubly reviewed and endorsed by the Scientific Committee of Ethics and Bioethics of the Universidad de Santiago de Cali (act # 03 of 2019). The protocol was classified as minimal risk and met all the requirements described by the Ministry of National Health [39].

Publishing consent

N/A

Conflict of interest

The authors declare that they have no conflict of interest.

Acknowledge

Not applicable.

References

1. Demir K, Akpınar E. The effect of mobile learning applications on students' academic achievement and attitudes toward mobile learning. MOJET. 2018;6:48–59. doi:10.17220/mojet.2018.02.004.

2. Osailan A. The relationship between smartphone usage duration (using smartphone's ability to monitor screen time) with hand-grip and pinch-grip strength among young people: an observational study. BMC Musculoskelet Disord. 2021;22:186. doi:10.1186/s12891-021-04054-6.

3. Osorio-Molina C, Martos-Cabrera MB, Membrive-Jiménez MJ, Vargas-Roman K, Suleiman-Martos N, Ortega-Campos E, Gómez-Urquiza JL. Smartphone addiction, risk factors and its adverse effects in nursing students: A systematic review and meta-analysis. Nurse Educ Today. 2021;98:104741. doi:10.1016/j.nedt.2020.104741.

4. Konok V, Liszkai-Peres K, Bunford N, Ferdinandy B, Jurányi Z, Ujfalussy DJ, et al. Mobile use induces local attentional precedence and is associated with limited socio-cognitive skills in preschoolers. Computers in Human Behavior. 2021;120:106758. doi:10.1016/j.chb.2021.106758.

5. Joo E, Kononova A, Kanthawala S, Peng W, Cotten S. Smartphone Users' Persuasion Knowledge in the Context of Consumer mHealth Apps: Qualitative Study. JMIR Mhealth Uhealth. 2021;9:e16518. doi:10.2196/16518.

6. Mergany NN, Dafalla A-E, Awooda E. Effect of mobile learning on academic achievement and attitude of Sudanese dental students: a preliminary study. BMC Med Educ. 2021;21:121. doi:10.1186/s12909-021-02509-x.

7. Wilkerson GB, Acocello SN, Davis MB, Ramos JM, Rucker AJ, Hogg JA. Wellness Survey Responses and Smartphone App Response Efficiency: Associations With Remote History of Sport-Related Concussion. Percept Mot Skills. 2021;128:714–30. doi:10.1177/0031512520983680.

8. Kwon SE, Kim YT, Suh H, Lee H. Identifying the mobile application repertoire based on weighted formal concept analysis. Expert Systems with Applications. 2021;173:114678. doi:10.1016/j.eswa.2021.114678.

9. Villota Enríquez JA, editor. Tecnología, sociedad y educación: desafíos de las Tic en el desarrollo social y sus implicaciones en la práctica educativa: Editorial Universidad Santiago de Cali; 2019.

10. Shaygan M, Jaberi A. The effect of a smartphone-based pain management application on pain intensity and quality of life in adolescents with chronic pain. Sci Rep. 2021;11:6588. doi:10.1038/s41598-021-86156-8.

11. Sohn SY, Krasnoff L, Rees P, Kalk NJ, Carter B. The Association Between Smartphone Addiction and Sleep: A UK Cross-Sectional Study of Young Adults. Front Psychiatry. 2021;12:629407. doi:10.3389/fpsyt.2021.629407.

12. Hitti E, Hadid D, Melki J, Kaddoura R, Alameddine M. Mobile device use among emergency department healthcare professionals: prevalence, utilization and attitudes. Sci Rep. 2021;11:1917. doi:10.1038/s41598-021-81278-5.

13. Thornton L, Gardner LA, Osman B, Green O, Champion KE, Bryant Z, et al. A Multiple Health Behavior Change, Self-Monitoring Mobile App for Adolescents: Development and Usability Study of the Health4Life App (Preprint); 2020.

14. Abadiyan F, Hadadnezhad M, Khosrokiani Z, Letafatkar A, Akhshik H. Adding a smartphone app to global postural re-education to improve neck pain, posture, quality of life, and endurance in people with nonspecific neck pain: a randomized controlled trial. Trials. 2021;22:274. doi:10.1186/s13063-021-05214-8.

15. Maharjan SM, Poudyal A, van Heerden A, Byanjankar P, Thapa A, Islam C, et al. Passive sensing on mobile devices to improve mental health services with adolescent and young mothers in low-resource settings: the role of families in feasibility and acceptability. BMC Med Inform Decis Mak. 2021;21:117. doi:10.1186/s12911-021-01473-2.

16. Freitas BHBM de, Gaíva MAM, Bernardino FBS, Diogo PMJ. Smartphone Addiction in Adolescents, part 2: Scoping Review—Prevalence and Associated Factors. Trends in Psychol. 2021;29:12–30. doi:10.1007/s43076-020-00040-4.

17. Warsaw RE, Jones A, Rose AK, Newton-Fenner A, Alshukri S, Gage SH. Mobile Technology Use and Its Association With Executive Functioning in Healthy Young Adults: A Systematic Review. Front Psychol. 2021;12:643542. doi:10.3389/fpsyg.2021.643542.

18. Choi S, Kim M, Kim E, Shin G. Changes in Low Back Muscle Activity and Spine Kinematics in Response to Smartphone Use During Walking. Spine (Phila Pa 1976). 2021;46:E426-E432. doi:10.1097/brs.0000000000003808.

19. Yue H, Zhang X, Sun J, Liu M, Li C, Bao H. The relationships between negative emotions and latent classes of smartphone addiction. PLoS One. 2021;16:e0248555. doi:10.1371/journal.pone.0248555.

20. Annoni AM, Petrocchi S, Camerini A-L, Marciano L. The Relationship between Social Anxiety, Smartphone Use, Dispositional Trust, and Problematic Smartphone Use: A Moderated Mediation Model. Int J Environ Res Public Health 2021. doi:10.3390/ijerph18052452.

21. Conlin M-C, Sillence E. Exploring British Adolescents' Views and Experiences of Problematic Smartphone Use and Smartphone Etiquette. JGI 2021. doi:10.4309/jgi.2021.46.14.

22. Chen P-L, Pai C-W. Pedestrian smartphone overuse and inattentional blindness: an observational study in Taipei, Taiwan. BMC Public Health. 2018;18:1342. doi:10.1186/s12889-018-6163-5.

23. Gamero K, Flores C, Arias WL, Ceballos KD, Román A, Marquina E. Estandarización del Test de Dependencia al Celular para estudiantes universitarios de Arequipa. Persona. 2017;0:179. doi:10.26439/persona2016.n019.979.

24. Azizi A, Pleimling M. A cautionary tale for machine learning generated configurations in presence of a conserved quantity. Sci Rep. 2021;11:6395. doi:10.1038/s41598-021-85683-8.

25. Hohman F, Srinivasan A, Drucker SM. TeleGam: Combining Visualization and Verbalization for Interpretable Machine Learning; 2019.

26. Lu Y, Lu G, Li J, Zhang Z, Xu Y. Fully shared convolutional neural networks. Neural Comput & Applic. 2021;33:8635–48. doi:10.1007/s00521-020-05618-8.

27. Sarker IH, Kayes ASM, Watters P. Effectiveness analysis of machine learning classification models for predicting personalized context-aware smartphone usage. J Big Data 2019. doi:10.1186/s40537-019-0219-y.

28. Chóliz M. Mobile-phone addiction in adolescence: The Test of Mobile Phone Dependence (TMD). Prog Health Sci 2012, Vol 2, No1 Test Mobile Phone Addiction. 2012;2.

29. Verónica Villanueva Silvestre. PROGRAMA DE PREVENCIÓN DEL ABUSO Y LA DEPENDENCIA DEL TELÉFONO MÓVIL EN POBLACIÓN ADOLESCENTE [Tesis Doctoral]. España: UNIVERSITAT DE VALÈNCIA-Departamento de Psicología Básica; 2012.

30. Dimate AE, Rodríguez DC, Rocha AI. Percepción de desórdenes musculoesqueléticos y aplicación del método RULA en diferentes sectores productivos: una revisión sistemática de la literatura. revsal. 2017;49:57–74. doi:10.18273/revsal.v49n1-2017006.

31. Tolles J, Meurer WJ. Logistic Regression: Relating Patient Characteristics to Outcomes. JAMA. 2016;316:533–4. doi:10.1001/jama.2016.7653.

32. Vapnik V. Statistical learning theory. New York: John Wiley and Sons; 1998.

33. Anuja Priyama and Saurabh Srivastava. Comparative Analysis of Decision Tree Classification Algorithms: International Journal of Current Engineering and Technology; 2013.

34. Breiman L. Using Iterated Bagging to Debias Regressions. Machine Learning. 2001;45:261–77. doi:10.1023/A:1017934522171.

35. Duda RO, Hart PE, Stork DG. Pattern classification. 2nd ed. New York: Wiley; 2001.

36. Bishop CM. Pattern recognition and machine learning. New York: Springer; 2006.

37. Kumar R, Indrayan A. Receiver operating characteristic (ROC) curve for medical researchers. Indian Pediatr. 2011;48:277–87. doi:10.1007/s13312-011-0055-4.

38. Fletcher RH, Fletcher SW, Fletcher GS. Clinical epidemiology: The essentials. 5th ed. Philadelphia: Wolters Kluwer/Lippincott Williams & Wilkins Health; 2019.

39. RESOLUCIÓN Nº 008430 DE 1993.

40. Laurence PG, Busin Y, Da Cunha Lima HS, Macedo EC. Predictors of problematic smartphone use among university students. Psicol Reflex Crit. 2020;33:8. doi:10.1186/s41155-020-00147-8.

41. Ivanova A, Gorbaniuk O, Błachnio A, Przepiórka A, Mraka N, Polishchuk V, Gorbaniuk J. Mobile Phone Addiction, Phubbing, and Depression Among Men and Women: A Moderated Mediation Analysis. Psychiatr Q. 2020;91:655–68. doi:10.1007/s11126-020-09723-8.

42. Zhao SZ, Luk TT, Guo N, Wang MP, Lai AYK, Wong BYM, et al. Association of Mobile Instant Messaging Chat Group Participation With Family Functioning and Well-Being: Population-Based Cross-sectional Study. J Med Internet Res. 2021;23:e18876. doi:10.2196/18876.

43. Xie YJ, Cheung DS, Loke AY, Nogueira BL, Liu KM, Leung AY, et al. Relationships Between the Usage of Televisions, Computers, and Mobile Phones and the Quality of Sleep in a Chinese Population: Community-Based Cross-Sectional Study. J Med Internet Res. 2020;22:e18095. doi:10.2196/18095.

44. Jeong Y-W, Han Y-R, Kim S-K, Jeong H-S. The frequency of impairments in everyday activities due to the overuse of the internet, gaming, or smartphone, and its relationship to health-related quality of life in Korea. BMC Public Health. 2020;20:954. doi:10.1186/s12889-020-08922-z.

45. Romero-Rodríguez J-M, Aznar-Díaz I, Marín-Marín J-A, Soler-Costa R, Rodríguez-Jiménez C. Impact of Problematic Smartphone Use and Instagram Use Intensity on Self-Esteem with University Students from Physical Education. Int J Environ Res Public Health 2020. doi:10.3390/ijerph17124336.

46. Balogun FM, Olatunde OE. Prevalence and predictors of problematic smart phone use among pre-varsity young people in Ibadan, Nigeria. Pan Afr Med J. 2020;36:285. doi:10.11604/pamj.2020.36.285.18858.

47. Vaterlaus JM, Aylward A, Tarabochia D, Martin JD. “A smartphone made my life easier”: An exploratory study on age of adolescent smartphone acquisition and well-being. Computers in Human Behavior. 2021;114:106563. doi:10.1016/j.chb.2020.106563.

48. Forster M, Rogers C, Sussman SY, Yu S, Rahman T, Zeledon H, Benjamin SM. Adverse childhood experiences and problematic smartphone use among college students: Findings from a pilot study. Addict Behav. 2021;117:106869. doi:10.1016/j.addbeh.2021.106869.

49. Tangmunkongvorakul A, Musumari PM, Tsubohara Y, Ayood P, Srithanaviboonchai K, Techasrivichien T, et al. Factors associated with smartphone addiction: A comparative study between Japanese and Thai high school students. PLoS One. 2020;15:e0238459. doi:10.1371/journal.pone.0238459.

50. Merma-Molina G, Gavilán-Martín D, Álvarez-Herrero J-F. Education for Sustainable Development: The Impact of the Values in Mobile Phone Addiction. Sustainability. 2021;13:1479. doi:10.3390/su13031479.

51. Cha S-S, Seo B-K. Smartphone use and smartphone addiction in middle school students in Korea: Prevalence, social networking service, and game use. Health Psychol Open. 2018;5:2055102918755046. doi:10.1177/2055102918755046.

52. Mustafaoglu R, Yasaci Z, Zirek E, Griffiths MD, Ozdincler AR. The relationship between smartphone addiction and musculoskeletal pain prevalence among young population: a cross-sectional study. Korean J Pain. 2021;34:72–81. doi:10.3344/kjp.2021.34.1.72.

53. Al-Hadidi F, Bsisu I, AlRyalat SA, Al-Zu'bi B, Bsisu R, Hamdan M, et al. Association between mobile phone use and neck pain in university students: A cross-sectional study using numeric rating scale for evaluation of neck pain. PLoS One. 2019;14:e0217231. doi:10.1371/journal.pone.0217231.

54. Thapa K, Lama S, Pokharel R, Sigdel R, Rimal SP. Mobile Phone Dependence among Undergraduate Students of a Medical College of Eastern Nepal: A Descriptive Cross-sectional Study. JNMA J Nepal Med Assoc. 2020;58:234–9. doi:10.31729/jnma.4787.

55. Baabdullah A, Bokhary D, Kabli Y, Saggaf O, Daiwali M, Hamdi A. The association between smartphone addiction and thumb/wrist pain: A cross-sectional study. Medicine (Baltimore). 2020;99:e19124. doi:10.1097/MD.0000000000019124.

56. Ismaeel FT. The Impact of Smart Phones on Musculoskeletal Pain on Students in Tikrit University. Ind. Jour. of Publ. Health Rese. & Develop. 2019;10:553. doi:10.5958/0976-5506.2019.01629.2.

57. Toh SH, Coenen P, Howie EK, Smith AJ, Mukherjee S, Mackey DA, Straker LM. A prospective longitudinal study of mobile touch screen device use and musculoskeletal symptoms and visual health in adolescents. Appl Ergon. 2020;85:103028. doi:10.1016/j.apergo.2019.103028.

Figures

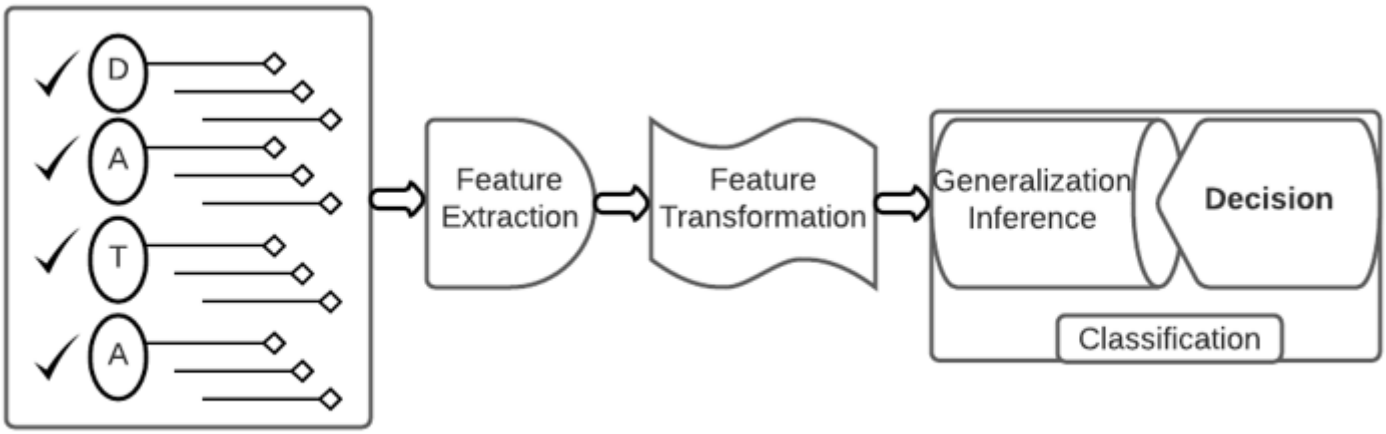

Figure 1

Automatic system for predicting smartphone dependency.

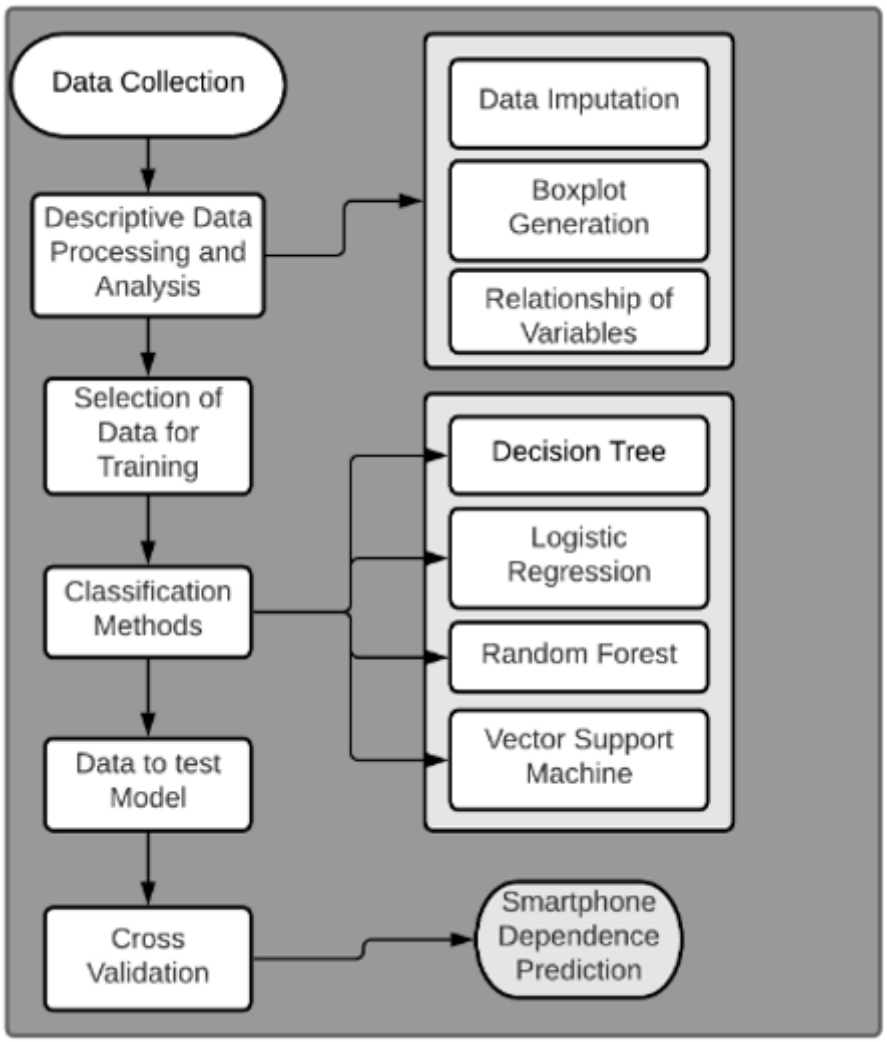

Figure 2

Information processing flowchart to find out the model.

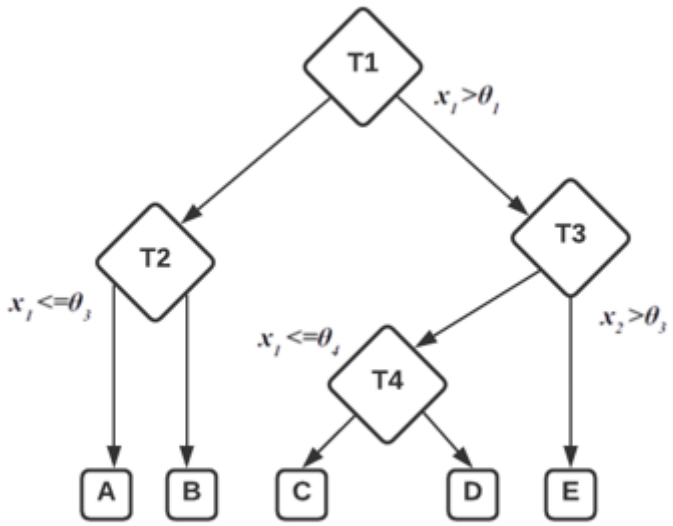

Figure 3

Decision tree.

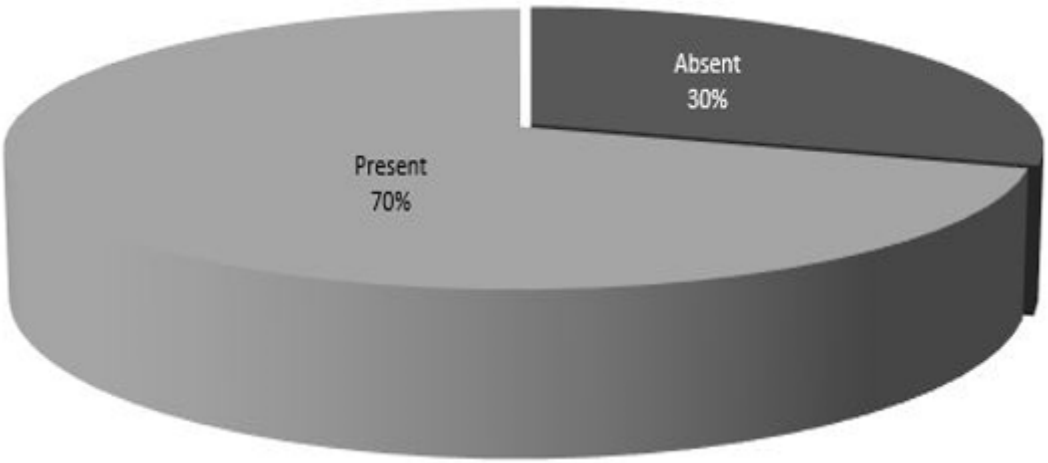

Figure 4

Frequency in response-variable percentage

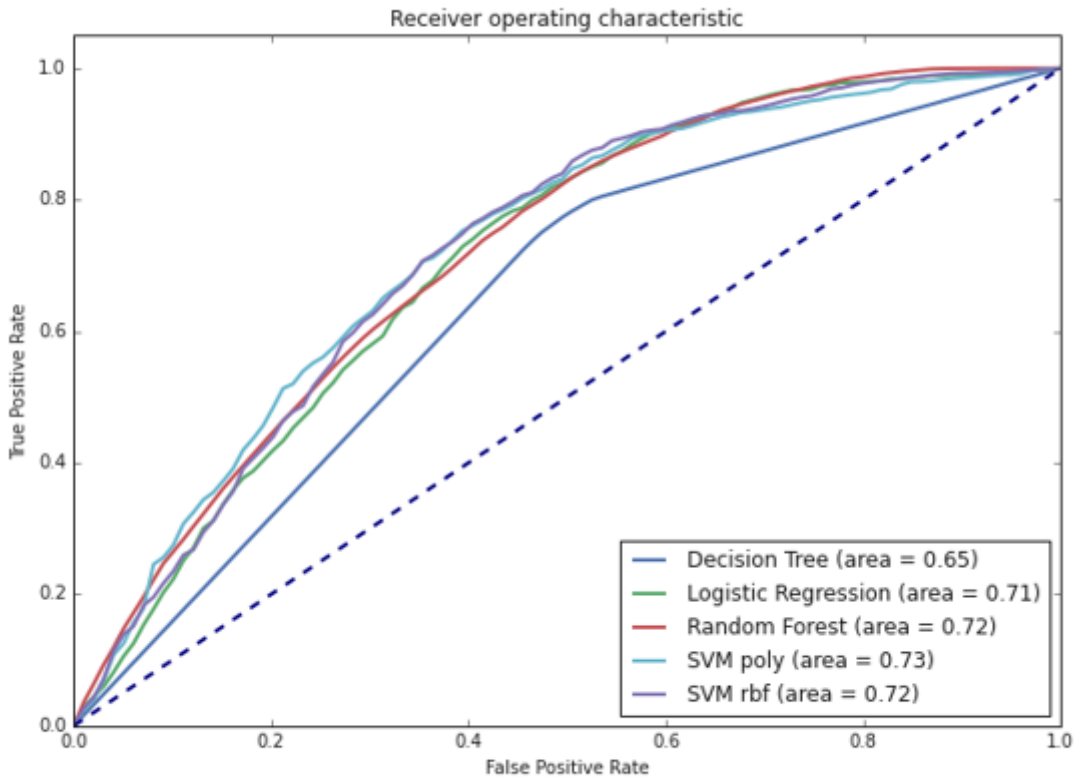

Figure 5

Receiver Operating Characteristic Curve (ROC curve) for all classification systems