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Role of self-regulation in controlling cyber loafing and smartphone addiction: Reducing health risk at the university level

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Abstract:

CONTEXT: Mobile phones have evolved into tools providing a virtual environment and frequently used for remote teaching strategies. Besides its unavoidable alternative in different situations, excessive use of the mobile phone has changed behaviors and influences interpersonal relationships and may also have a harmful impact on health and happiness. To overcome these issues, several approaches have been introduced to identify and minimize the smartphone addiction. Literature reveals that self-regulation, smartphone usage, cyberloafing, and general self-efficacy have a prominent role in mobile phone addiction.

AIMS: The aims of the current study were to analyze and optimize the role of considered factors to overcome the excess mobile phone usage and its addiction.

METHODS AND MATERIAL: Using the random sampling technique, an adopted questionnaire was utilized to collect data of 500 university level students. The target population consisted of 5000 university level students.

STATISTICAL ANALYSIS USED: A complete and comprehensive model was established using structural equation modeling.

RESULTS: Findings revealed that there is a significantly negative effect of self-regulation on both cyberloafing and addiction, while smartphone usage has a positive effect on smartphone addiction. Similarly, self-efficacy positively affected the cyberloafing, resulting in positive effects on the smartphone addiction.

CONCLUSIONS: Awareness, smartly planned lessons, learning materials, recommended applications, and restricted technologies can be effective in controlling the smartphone addiction and their health-related problems. Additional factors such as students' disengagement from tasks, lack of context familiarities, and the boring nature of the task or teaching method may increase the mobile addiction. For this, extra curriculum activities and support programs can significantly reduce the mobile use.

Keywords:

Mobile learning, online class, self-efficacy, self-regulation, smartphone addiction

Introduction

After coronavirus disease 2019 (COVID-19) pandemic, institutions frequently use remote teaching strategies to save resources and students' time and maintain the quality of education.[1,2] Consequently, smartphone and online education gains an important and unavoidable place in students' life globally.[3,4] Due to the excessive usage, mobile phones have changed behaviors and influence interpersonal relationships

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and may also have a harmful impact on health and happiness.[5,6] Misuse and improper use are considered as significant indicators, indicating that someone is on the verge of developing a smartphone addiction.[7-9] It causes a wide range of direct and indirect issues regarding mental health, academic progress, and interpersonal relationship.[10-12] Moreover, authors noticed smart phone addiction caused disruptive attempts to connect with others, psychiatric disorders, and disruption in routine work.[13-15] Smartphone addiction is however behavior-based and therefore differs from drug-based psychological addiction like alcohol or opioid addiction.[16] Literature shows that several variables have been highlighted as causes of addiction, such as user characteristics, stress, and period of mobile usage.[17,18] Other researchers observed that it may have an impact on students' academic performance.[19,20]

From the literature, several variables were identified, which could play a prominent role in analysing smartphone addiction. These include cyberloafing, mobile phone usage, self-regulation, and self-efficacy. Regular use of smartphone influences the addiction.[21,22] The irrelevant browsing activity "cyberloafing" during office or class working hours yielded a negative impact on academic performance.[23,24] Similarly, beliefs like self-regulations and "individual's emotions" are effective to control detraction and general self-efficacy may also be effective to make control over difficult tasks and on their own performance.[25,26] Overall, this study has conducted to investigate reasons behind increasing trends of smartphone addiction among university students by checking the role of general self-efficacy, cyberloafing, and smartphone usage on smartphone addiction. The second aim was to optimize these factors to continue remote teaching strategies with reduced mobile usage and addiction. Figure 1 illustrates the conceptual framework for the current study.

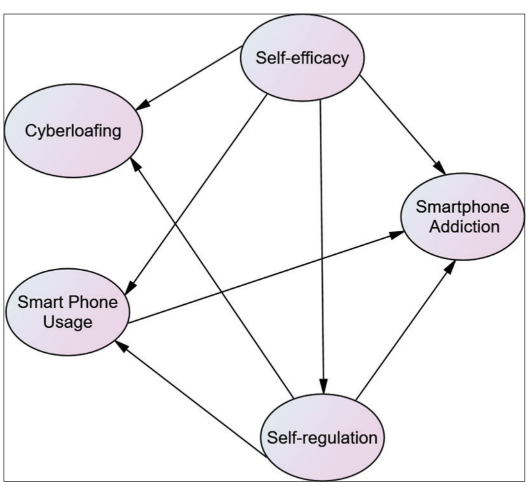

Figure 1: Proposed conceptual framework

Significance of the study

This work would add useful literature for several variables causing mobile addiction during or after remote teaching and their related problems. Understanding how students' self-regulation can control both cyberloafing and smartphone addiction can motivate teachers to seek additional resources to improve their teaching practices. The result of the research would cover the gap to offer crucial insights that remained uncovered. This research would also underline some important implications for educational reform, policy formulation, curriculum development, teacher training, and comprehensive development of students.

Materials and Methods

For the current study, three public universities' undergraduate students were chosen. The total population comprised 5000 students, including 2499 males and 2501 females. Using the random sampling technique, a sample size of 500 was taken, including 44% of the male participants and 56% of the female participants. This study has been carried out during 2023–2024. In addition, the pilot test was also carried out using data of 50 participants. A questionnaire was used to collect data.

Research instrument

Data were gathered through "Self-regulation Scale," "General self-efficacy scale," "Smartphone addiction scale," and "Cyberloafing scale". In order to measure self-regulation, the self-regulation scale was adapted.[27] Furthermore, to determine the level of cyberloafing behavior of university students, the social purposeful cyberloafing scale was adopted.[28] Likewise, for the assessment of smartphone addiction severity, the smartphone addiction scale was used.[29] In addition, the smart smartphone use scale was also adapted.[30]

To validate the questionnaire's item, a preliminary pilot study was carried out before conducting the final survey. A total of 50 students from the target group were chosen randomly. To assess the internal reliability of the constructions' components, the Cronbach's alpha was used. All the items showed reliability values above 0.7 meeting the recommended threshold.[31] Therefore, all items' reliable values were deemed acceptable for further analysis.

Data collection and analysis

The evaluation of the study model comprised three phases. In the first phase, exploratory factor analysis (EFA) was run in order to identify the underlying structure of a substantial number of items. The second phase was carried out to assess the descriptive statistics, reliability, convergent validity, and discriminant validity of the measured items according to the proposed model. Last, the structural model evaluation using structural equation modeling (SEM) was tested.

Ethical considerations

This study was carried out under NUML University approved code (1568696934/R. Ethics/NUML). Participants were well informed about the purpose and requested to give their consents to participate in this work.

Results

Descriptive statistics

Prior to data processing., the data set was assessed for missing data, sampling size, multivariate and univariate normality, outliers, and multicollinearity. Table 1 shows descriptive data for each construct. The kurtosis ranged from -.007 to -.079, whereas the skewness ranged from -.753 to -1.19. Skew and kurtosis indices should be below 3.0 and 10, respectively. Therefore, the data were considered as normal for all the variables.[32] To evaluate our model, SEM was utilized in two steps.

Analysis of measurement model

The measurement model evaluation procedures were employed to verify the validity and reliability of the measurements. Hair Jr, Matthews[33] proposed three distinct approaches, including convergent validity, indicator loadings, and internal consistency reliability, with discriminant validity to validate the measurement model. First, to evaluate the scale items' convergent validity based on factor loadings, researchers suggested that the factor loading should be higher than 0.50. As a result, we removed those items having low factor loadings (<0.50) from the scales. All the items were taken into consideration for our study range between .50 and .88, indicating convergent validity at the item level as shown in Table 2. Second, we analyzed each construct's reliability. The reliability of each construct was measured through Cronbach's alpha, which provides verification for the proposed model's convergent validity as shown in Table 2. The third approach is to ensure that each construct's average variance extracted (AVE) is more than 0.50.[34] All constructions had AVE values greater than the 0.50 threshold.

Internal consistency reliability and indicator loadings

Table 3 shows that selected factors are reliable since the composite reliability was higher than the minimum threshold of 0.70. Table 3 also indicates about the convergent validity. Since the AVE value for each variable was greater than 0.50, the model had attained convergent validity.

Table 1: Descriptive statistics showing normality of data

Construct	Mean value	Standard Deviation	Skewness	Kurtosis
SRL	14.9	5.6	-0.007	-1.19
SLF	21.7	6.5	-0.179	-0.753
SD	15.5	4.8	-0.079	-0.88
CL	24.0	7.8	-0.09	-1.16
SMU	88.2	29.7	-0.083	-0.983

SRL: self-regulated, SLF: self-efficacy, SD: smart phone addiction, CL: cyberloafing, SMU: smartphone usage

Table 2: Factor loading, Cronbach's alpha, and CR of the measurement model

Constructs	Items	Item loadings	Cronbach's alpha	CR
Smartphone addiction (SD)	SAD_2	0.79	0.88	0.91
	SAD_3	0.88		
	SAD_4	0.85		
	SAD_5	0.87		
Self-regulation (SRL)	SR_1	0.88	0.93	0.95
	SR_2	0.93		
	SR_3	0.87		
	SR_4	0.90		
	SR_5	0.90		
Self-Efficacy (SL)	SLF_1	0.85	0.90	0.92
	SLF_2	0.88		
	SLF_3	0.84		
	SLF_5	0.84		
	SLF_7	0.82		
Cyberloafing (CL)	$Cyber_1$	0.83	0.90	0.92
	$Cyber_2$	0.87		
	$Cyber_3$	0.87		
	$Cyber_4$	0.81		
	$Cyber_5$	0.79		
	$Cyber_6$	0.70		
	$Cyber_8$	0.61		
Smartphone Usage (SMU)	SMART 2	0.80	0.91	0.93
	SMART 4	0.81		
	SMART 6	0.83		
	SMART 7	0.87		
	SMART 8	0.80		
	SMART 9	0.84		
	SMART 10	0.83		
	SMART 13	0.80		

SRL: self-regulated, SLF: self-efficacy, SD: smart phone addiction, CL: cyberloafing, SMU: smartphone usage

After achieving a measuring model, the discriminant validity was evaluated. Usually, a construct's discriminant validity measures how different it is from other constructs.[34] If the correlation between the constructs is less than the square root of AVE, the entire model has discriminant validity. However, each AVE square root must be smaller than the interconstruct.[35] Since the correlations were less than the diagonal values, all components exhibited acceptable discriminant validity [Table 2]. Likewise, the proposed model has also shown discriminant validity.

The AVE value was within the recommended range.[33] Table 3 shows the correlation between constructs together with square root of corresponding AVE. In addition, items showed significant loading on their specified factor and have low cross-loadings with the remaining factors. Overall, all items indicated good convergent and discriminant validity. Overall, the reflecting model shows that it satisfied with all reliability criteria. To assess the validity of the suggested measurement structures, CFA was conducted. Multiple variables were used to fit the proposed CFA model. Various goodness-of-fit indices were used in SEM to assess how well a model fits the data.

Equation model tests with the structural model

Generally, model fitting is measured using a number of indices in SEM research studies. For the current proposed model, the Chi-square, goodness-of-fit index (GFI), comparative fit index (CFI), and root mean square error of approximation (RMSEA) were computed. The obtained values from the model's first run were $\chi^2 = 2786$, df = 369, $P < .000$, CMIN/DF = 7.5, CFI = 0.81, GFI = 0.72, TLI =.80, and RMSEA = .115. The RMSEA for the current model was above 0.100. An index close to 0.10 indicates good fit.[36] The current findings demonstrate that an RMSEA fit value greater than 0.01 indicated the model's marginality. Therefore, the model was modified by removing the invalid constructs.[37] Additionally, the model was modified by including a covariance between the items with the highest modification index (MI) values because it did not fit the data well. Findings showed that the item SAD1 had a low factor loading. Due to their low factor loading, items were gradually removed from the initial measurement model.[38]

Analysis of the structural model

After adding covariant-related items, goodness-of-fit statistics generated somewhat improved fit values as shown in Figure 2, which illustrates that the overall SEM model and the data were turned into a compatible form.

The major outcomes of the model represented in Figure 2 are summarized in Table 4. The final model was considered to be suitable for structural modeling as a result of the modification's implementation because it provided the best data fit values, Figure 3. Overall, the model was verified to be valid and reliable. Based on the dimensional structure of the latent variable, the effects of hypothesis in the theoretical model were analyzed.

Assessment of the structural model and hypotheses testing

The structural model assessment usually covers several stages.[34] The first step in determining collinearity is reporting the variance inflation factor (VIF). Other major steps include determining the coefficient of determination (R^2) and predictive significance in the structural model. The variance of inflation values in the current study were all below 5.0, indicating that the model has no multicollinearity problem. Moreover, predictive explanatory power (R^2) indicated how well the dependent variables are explained by dependent variables. Sarstedt, Hair Jr[44] illustrated it as the model's in-sample predictive ability. R^2 ranges from 0 to 1. A higher value denotes a higher level of R^2. 0.25 is considered a weak value, whereas the moderate and significant values are 0.50 and 0.75, respectively. The current study model showed 75%, which is a good and significant predictive value, indicating that the structural model satisfies all model fit indices.

Table 3: Correlation between constructs illustrated together with square root of corresponding AVE

	AVE	SD	CL	SMU	SE
SD	0.72				
CL	0.76	0.62			
SMU	0.71	0.54	0.68		
SE	0.72	0.63	0.70	0.69	
SRL	0.82	0.55	0.59	0.65	0.80

SMU: smart phone usage, SD: smartphone addiction, SRL: self-regulation, CL: cyberloafing, SL: self-efficacy

Table 4: Confirmatory factor analysis of final model

Fit Indices	Criteria Limit	Current model results	Explanation	References
Absolute Fit Measure				
Chi Square	$<\chi^2$ α; df	1812		[39]
CMIN/DF	≤5.0	5.0	Good	[39]
Probability	≤0.05	0.00	Good	[39]
GFI	≥0.90	0.90	Good	[40]
RMSEA	<.10	0.09	Good	[40]
Incremental Fit Measure				
TLI	≥0.90	0.90	Good	[41]
NFI	≥0.90	0.90	Good	[42]
CFI	≥0.90	0.90	Good	[42]
Parsimonious Fit Measures				
PNFI	>0.50	0.74	Good	[43]
PGFI	>0.50	0.76	Good	[43]

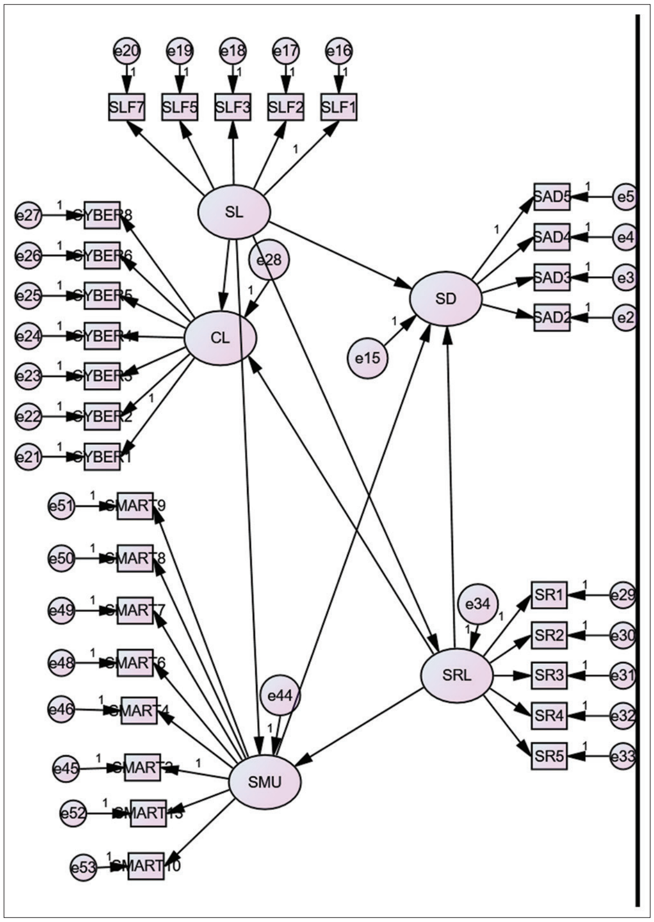

Figure 2: The modification based on the modification Indices. Note. SMU: smart phone usage, SD: smartphone addiction, SRL: self-regulation, CL: cyberloafing, SL: self-efficacy

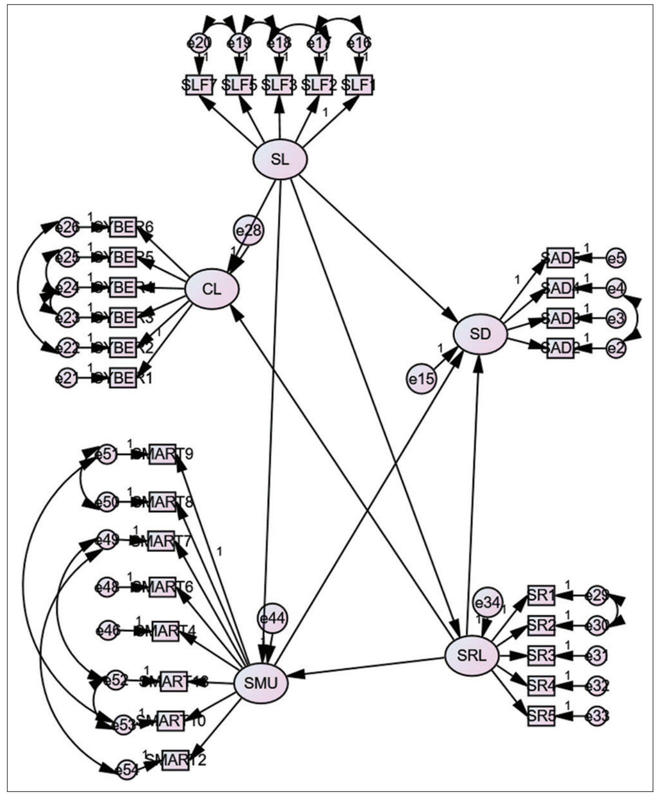

Figure 3: Path coefficient findings of the selected parameters. Note. SMU: smart phone usage, SD: smartphone addiction, SRL: self-regulation, CL: cyberloafing, SL: self-efficacy

Table 5: Path analysis of latent variables and comparisons with proposed hypotheses

Casual Paths	Estimate	SE	C.R	*P*	Decision and Result
H_1: SD <- SMU	-0.359	0.111	-3.288	***	Not Supported
H_2: SD <- SRL	-1.36	0.288	-4.726	***	Supported
H_3: CL <- SRL	-1.709	0.274	-6.236	***	Supported
H_4: CL <- SL	2.248	0.258	8.715	***	Supported
H_5: SMU <- SRL	-0.764	0.176	-4.348	***	Supported
H_6: SD <- SL	2.098	0.322	6.52	***	Supported
H_7: SRL <- SL	0.899	0.045	20.127	***	Supported
H_8: SMU <- SL	1.366	0.171	7.976	***	Not Supported

SMU=smart phone usage, SD=smartphone addiction, SRL=self-regulation, CL=cyberloafing, SL=self-efficacy

Assessing statistical significance of hypothesized paths

In the next phase, the standardized path coefficient was calculated through regression and the related t-values. For this purpose, a bootstrapping procedure with 5000 iterations was used. Table 5 demonstrates that smartphone usage has a significant direct relationship with smartphone addiction, self-regulation, and self-efficacy. It has also been observed that self-regulation and self-efficacy have significant effects on smartphone addiction. Additionally, it was found that self-regulation and self-efficacy had a substantial direct impact on cyberloafing behavior. Moreover, self-regulation directly affects self-efficacy.

Discussion

The main aim of this work was twofold. The first aim was to explore the potential role of mobile usage, self-regulation, general self-efficacy, and cyberloafing in smart phone addiction. The second aim was to optimize these factors to continue remote teaching strategies with reduced mobile usage and addiction. Further elaboration on these objectives is provided in the subsequent sections.

Examining the impact of self-regulation on smartphone addiction

Results of the current study also show negative and significant relationship (β = -1.36) between self-regulation and smart phone addiction [Table 5]. Therefore, it can be concluded that students having higher self-regulation skills tend to exhibit lower addictive smartphone behaviors. Addictive behavior often stems from a lack of self-control. In such a scenario, it can be assumed that when students have difficulty in regulating their mobile usage, they are more likely to have smartphone addiction.[26,45] Therefore, authors Van

Deursen and Bolle[46] suggested that enhancing students' self-regulation skills might be successful in reducing or overcoming this addiction.

Examining the impact of cyberloafing on smartphone addiction

Results have shown a significant and positive effect of cyberloafing (β = 0.211) on smartphone addiction values. However, a few researchers have studied these two variables together. However, Andreassen and Billieux[47] suggested that students who engage in cyberloafing activities in the classroom are more likely to develop mobile addiction. Distraction in the classroom environment has risen as a result of smartphones.[2,9] Therefore, authors argued that cyberloafing, which is defined as the use of smartphones in a classroom setting for activities pertaining to learning activities, may have a negative impact on students' learning processes. Moreover, smartphone apps such as social networking sites (SNSs) stimulate cyberloafing behavior, which can lead to smartphone addiction.[13,48] Therefore, the researchers have noticed that social network use affects both variables; hence, researchers have suggested that the importance of social networks, especially in the lives of young people, should be recognized.[49]

Examining the impact of smartphone usage on smartphone addiction

Results indicated that smartphone usage has a negative significant effect (β = -0.359) on smartphone addiction. Therefore, it can be concluded that students had used smartphone for solving their tasks, assignments, and research work. Excessive use might have disappointed them, and they were ready to quit.[50] In some cenarios, due to the external environment, gender, and nature of responsibility, people may be ready to quit the exessive use, resulting in less addiction. Other possible reasons might be the availability of limited data. These findings are aligned with the findings of other researchers. As smartphone usage increases, there is likely a corresponding rise in the tendency toward addiction.[51,52] Addictive users cannot control their addictive behavior.[25] Therefore, authors suggested that with the growing rate of smartphone use in today's world, it is crucial to keep this rate under control. Moreover, smartphone-addicted users may restrict their ability to interact with family and community, and it affects their academic achievements as they show a diminished level of concentration.[53-55] Moreover, Samaha and Hawi[20] also noticed a negative impact of smartphone uses in academic success (CGPA). Therefore, authors suggested that during learning activities, students' phone use should be monitored, restricted, and prohibited. In a recent report, an application was proposed to assist smartphone use to be controlled.

Explanation for negative and significant effects of self-regulation on cyberloafing

Findings revealed that self-regulation has shown negative and significant effects on cyberloafing, while general self-efficacy has positive effects on cyberloafing. It means general self-efficacy boosts the cyberloafing, resulting in increased mobile addiction. However, self-regulation mitigates the mobile addiction through controlling cyberloafing. In the case of self-regulation via cyberloafing, negative and significant effects (β = -1.709) were observed on mobile addiction. The possible reason is the high level of self-control, which is also mainly influenced by self-regulation. Due to these high levels of concentration and self-control, students were not distracted, resulting in decreased cyberloafing and addiction. Findings are well aligned with previous studies. Kanthawongs and Jabutay[56] suggested that lack of ability of self-regulation may have serious consequences, which in turn leads to a rise in students' media consumption.

Implications

The result of the research had covered the gap to offer crucial insights that remained uncovered. This research has important implications for educational reform, policy formulation, curriculum development, teacher training, and comprehensive development of students. Understanding how students' self-regulation can control both cyberloafing and smartphone addiction can motivate teachers to seek additional resources to improve their teaching practices.

One possible reason in increasing the cyberloafing behavior which can lead to smartphone addiction is less engagement of the students in their tasks, poorly planned classes, or uninteresting teaching methods. Therefore, teachers should focus on engagements of their students through making the state-of-art classes with interesting tasks. Inquiry-oriented classes and group discussions to learn and elaborate tasks should be encouraged. Students' engagements and involvements can be influenced by utilization of nonroutine nature of tasks, context familiarities, and activities. Such types of tasks utilize students' extra attention, efforts, and learning strategies to be solved and may reduce the mobile addition.

In addition to the smartly planned lessons and students' engagements, learning materials can be effective in controlling the smartphone addiction. Students should be encouraged to read books and utilize printed materials and notes. Utilization of library environments and labs can promote targeted and task-oriented study culture through updated but restricted technological-based approaches. Awareness through seminars, classrooms, noticeboards, and and so on about the harmful effects may reduce smartphone usage and their health-related problems. Extra curriculum activities and support programs can significantly reduce the mobile usage. It will help students to not only excel academically but also flourish physically and mentally.

Strengths and limitations of this work

In this study, sample size was a good representation of the population being studied, and it had allowed for generalization of the findings to similar populations. It is also worth noting that the sample was drawn from central universities and institutes, which had added to the diversity of the sample and provided more comprehensive insights into the factors affecting smartphone addiction at the university level in Pakistan. However, due to infrastructure and other facilities, data of remote and provincial universities might be different. In order to minimize the errors in self-reported data, participants' demographic information was compared and verified with institutional data.

Conclusions

The findings of the current study indicate that there is a significantly negative effect of self-regulation on both cyberloafing and addiction, while smartphone usage has positive effects on smartphone addiction. Similarly, self-efficacy positively affected the cyberloafing, resulting in positive effects on the smartphone addiction. Additional factors such as students' disengagement from tasks, lack of context familiarities, and boring nature of task or teaching method may increase the mobile addiction. Therefore, it could be useful to review the relation of these factors to further explain the students' addiction and achievements in academics. It might be useful to review the relationship of the nature of learning materials and smartly plan lessons/tasks to minimize the mobile usage and addiction.

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Conflicts of interest

There are no conflicts of interest.

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