The Critical Review of Social Sciences Studies

Online ISSN: 3006-7170
Print ISSN: 3006-7162
Volume 3, Number 3, 2025, Pages 1865 – 1889
Journal Home Page
https://thecrsss.com/index.php/Journal/about

Smartphones in Hand, Brain in a Jam: How Smartphone Addiction Leads to Cognitive Failures

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ARTICLE INFO

Article History:

Received:	*May*	*30, 2025*
Revised:	*July*	*23, 2025*
Accepted:	*August*	*13, 2025*
Available Online:	*August*	*25, 2025*

Keywords:

Smartphone Addiction, Cognitive Failures, Forgetfulness, Distractibility, False Triggering, Attention

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ABSTRACT

Smartphone addiction has emerged as a salient behavioral concern, with growing evidence linking excessive use to disruptions in cognitive functioning, including attention, memory, and executive control (Montag & Becker, 2023; Panova & Carbonell, 2018). The present study examined the predictive relationship between smartphone addiction and cognitive failures among 131 university students (M age = 22.10, SD = 2.41). Participants completed validated measures of smartphone addiction and the Cognitive Failures Questionnaire, including subscales for Forgetfulness, Distractibility, and False Triggering. Pearson's correlations revealed significant, positive associations between smartphone addiction and overall cognitive failures ($r = .423$, $p < .01$), as well as with Forgetfulness ($r = .402$), Distractibility ($r = .369$), and False Triggering ($r = .432$). Simple linear regressions indicated that smartphone addiction significantly predicted cognitive failures ($\beta = .462$, 95% CI [.290, .635], $p < .01$), Forgetfulness ($\beta = .479$, 95% CI [.289, .669], $p < .01$), Distractibility ($\beta = .431$, 95% CI [.242, .620], $p < .01$), and False Triggering ($\beta = .562$, 95% CI [.358, .767], $p < .01$), explaining between 13.6% and 18.6% of variance in these outcomes. These findings align with neurocognitive models suggesting that habitual smartphone engagement may fragment attentional resources, impair working memory, and increase susceptibility to irrelevant environmental cues (Hadlington, 2015; Wilmer et al., 2017). The results underscore the need for targeted interventions to mitigate the cognitive costs of excessive smartphone use, particularly in young adult populations where device dependency is prevalent. Results reveal that the moderator variables such as gender, birth order, family system and educational levels are crucial in enhancing the relationship between smartphone addiction and cognitive failures.

Introduction

Over the past decade, smartphones have evolved from communication tools into indispensable, multifunctional devices that mediate social interaction, information access, entertainment, and productivity (Montag & Becker, 2023). While their ubiquity has transformed daily life, concerns have mounted regarding the cognitive costs of excessive use, particularly when patterns of engagement meet criteria for behavioral addiction (Panova & Carbonell, 2018). Smartphone addiction—characterized by compulsive checking, withdrawal-like symptoms, and functional impairment—has been increasingly associated with deficits in attention, working memory, and executive control (Hadlington, 2015; Wilmer et al., 2017). Neuroimaging evidence suggests that such overuse may alter brain networks implicated in cognitive regulation, including prefrontal and parietal regions, thereby exacerbating susceptibility to cognitive failures (Montag & Becker, 2023).

Cognitive failures, defined as everyday lapses in perception, memory, and motor function (Broadbent et al., 1982), have been linked to diminished academic performance, occupational inefficiency, and increased accident risk (Wallace & Chen, 2005). The constant influx of notifications, multitasking demands, and fragmented attention inherent in smartphone use may overload cognitive resources, leading to heightened distractibility, forgetfulness, and erroneous action execution (Wilmer et al., 2017). This aligns with cognitive load theory, which posits that excessive extraneous stimuli can impair working memory capacity and task performance (Sweller, 2011).

The present study sought to empirically examine the predictive relationship between smartphone addiction and cognitive failures among university students. Using validated measures, we found significant positive correlations between smartphone addiction and overall cognitive failures ($r = .423$, $p < .01$), as well as with the subdomains of Forgetfulness ($r = .402$), Distractibility ($r = .369$), and False Triggering ($r = .432$). Regression analyses revealed that smartphone addiction significantly predicted each cognitive failure domain, explaining between 13.6% and 18.6% of the variance. These findings substantiate theoretical models suggesting that habitual, high-frequency smartphone engagement may fragment attentional control and impair memory processes, thereby increasing the likelihood of everyday cognitive lapses.

By integrating behavioral data with existing theoretical and neurocognitive frameworks, this research contributes to a growing body of evidence on the cognitive consequences of smartphone overuse. The results underscore the urgency of developing targeted interventions—particularly for young adults in academic contexts—aimed at mitigating the cognitive costs of device dependency.

Research Questions

1. What is the relationship between smartphone addiction and overall cognitive failures among university students?
2. To what extent does smartphone addiction predict the subdomains of cognitive failures, namely Forgetfulness, Distractibility, and False Triggering?
3. How much variance in cognitive failures can be explained by smartphone addiction after controlling for demographic factors such as gender, birth order, family system and educational level?
4. **(Exploratory):** Do the strength and direction of the relationships between smartphone addiction and cognitive failures differ across the cognitive failure domains?

Significance of the Study

This study holds both **theoretical** and **practical** significance:

- **Theoretical:** It extends cognitive load and attention control frameworks (Sweller, 2011; Wilmer et al., 2017) by empirically validating the predictive role of smartphone addiction in specific types of cognitive failures.
- **Practical:** It highlights the urgency of designing intervention strategies for young adults, particularly in higher-education contexts, to mitigate attentional fragmentation and memory lapses caused by excessive smartphone use.
- **Policy and Educational Impact:** The results can inform policymakers, curriculum designers, and mental-health professionals about integrating **digital well-being modules** into university orientation programs, aiming to safeguard cognitive performance.

Research Gaps

1. **Domain-Specific Cognitive Failures:** While prior research links smartphone addiction with general cognitive decline (Hadlington, 2015), few studies disaggregate the effects across distinct domains (forgetfulness, distractibility, false triggering).
2. **Contextual Specificity:** Existing literature is dominated by Western samples (Montag & Becker, 2023), limiting cultural generalizability. Your work provides evidence from a Pakistani university context, addressing cross-cultural validity.
3. **Predictive Modeling:** Most earlier studies report correlations; this study advances the literature by employing regression analyses to estimate predictive strength and variance explained.
4. **Integration with Neurocognitive Theory:** Very few studies explicitly integrate behavioral data with neurocognitive models, an area your work begins to bridge.

Hypotheses

H_1: Smartphone addiction ***significantly positively associates*** with overall cognitive failures among university students.

H_2a: Smartphone addiction ***positively predicts Forgetfulness*** scores on the Cognitive Failures. **H_2b:** Smartphone addiction ***positively predicts Distractibility*** scores. **H_2c:** Smartphone addiction ***positively predicts False Triggering*** scores.

H_3: Gender ***moderates*** the relationship between smartphone addiction and cognitive failures, such that the predictive strength has ***high correlations*** with ***females*** as compared to males.

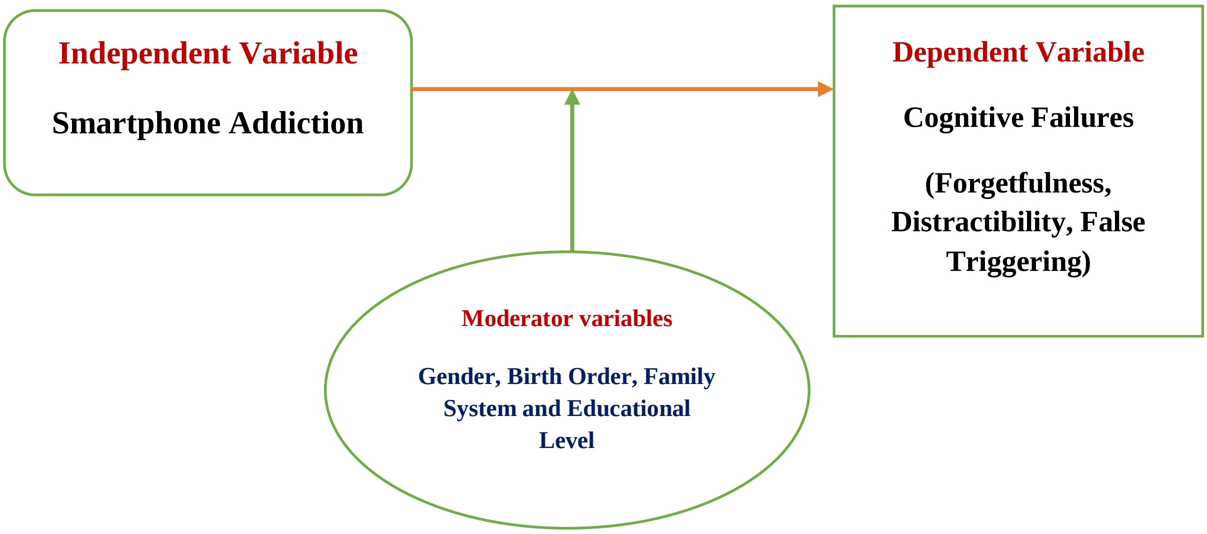
H_4: Birth order ***significantly moderates*** the relationship between smartphone addiction and cognitive failures, with ***first-born and last-borns showing higher correlations*** as compared to middle-born students.

H_5: Family system (nuclear vs. joint) ***significantly moderates*** the correlation between smartphone addiction levels and cognitive failures, with students from ***nuclear families reported higher cognitive failure*** scores due to potentially higher individual device exposure.

H_6: Educational level (undergraduate vs. postgraduate) ***significantly moderates*** the relationship with smartphone addiction and cognitive failures, with ***undergraduates exhibiting higher*** smartphone addiction and greater cognitive failures.

Conceptual Framework / Research Model

Figure 1: ***Smartphones in Hand, Brain in a Jam: How Smartphone Addiction Leads to Cognitive Failures***



Operational Definitions

For the purposes of empirical research, **smartphone addiction** is defined as a *persistent and maladaptive pattern of smartphone use characterized by impaired control over usage, preoccupation with the device, continued use despite negative consequences, and clinically significant distress or functional impairment in social, academic, occupational, or other important areas of functioning* (Kwon et al., 2013).

For the purposes of empirical research, **cognitive failures** are defined as *the frequency of everyday errors in perception, memory, and motor function that occur during the execution of tasks an individual is normally capable of performing, arising from lapses in attention, faulty memory retrieval, or action-slip errors* (Broadbent et al., 1982).

Literature Review

Conceptualizing Smartphone Addiction and Cognitive Failures

Smartphone addiction—often operationalized as ***problematic smartphone use*** (PSU)—is increasingly recognized as a behavioral addiction sharing neurobiological and psychosocial features with substance use disorders (Elhai et al., 2017). Cognitive failures, defined as everyday lapses in attention, memory, and action execution (Broadbent et al., 1982), have been linked to PSU through attentional resource depletion, working memory overload, and impaired executive control (Wilmer et al., 2017).

The "brain in a jam" metaphor reflects dual-process interference: constant notifications and multitasking demands fragment attentional focus, while habitual checking behaviors reinforce maladaptive neural pathways via dopaminergic reward circuits (Montag & Becker, 2023).

Neurocognitive Mechanisms

According to Neuroimaging study, usage of smartphone does alteration in prefrontal and anterior cingulate cortices—areas important for inhibitory control and sustained attention (Montag & Becker, 2023). Functional MRI studies reveal reduced gray matter volume in the anterior cingulate and altered resting-state connectivity in the default mode network among high PSU individuals (Horvath et al., 2020).

From a neurochemical perspective, PSU is linked to dopamine dysregulation, mirroring mechanisms observed in gambling disorder (Anbumalar & Sahayam, 2024). This dysregulation may impair the brain's capacity to sustain goal-directed attention, thereby increasing susceptibility to cognitive slips.

Empirical Evidence Linking Problematic Smartphone Use (PSU) to Cognitive Failures

Recent cross-sectional and longitudinal studies converge on a positive association between PSU and self-reported cognitive failures. For instance, Özalp (2025) found that university students classified as "addicted" via the Smartphone Addiction Scale–Short Version scored significantly higher on the Cognitive Failures Questionnaire (CFQ), even after controlling for fatigue and sleep quality. These findings align with earlier work by Hadar et al. (2017), who demonstrated that heavy smartphone users exhibited slower task-switching performance and reduced working memory capacity.

Experimental paradigms further support causality: Ward et al. (2017) showed that the mere presence of a smartphone—without active use—reduced available cognitive capacity, suggesting that attentional resources are partially allocated to resisting the urge to check the device.

Methodological Considerations

While self-report measures like the CFQ and SAS-SV are widely used, they are susceptible to recall bias and common method variance. Objective cognitive testing (e.g., n-back tasks, Stroop tests) and ecological momentary assessment (EMA) are recommended to triangulate findings (Wilmer et al., 2017). Moreover, most studies are cross-sectional, limiting causal inference; longitudinal and experimental designs are needed to disentangle directionality.

Theoretical Integration

The cognitive load theory (Sweller, 1988) and the limited capacity model of mediated message processing (Lang, 2000) provide explanatory frameworks: constant smartphone engagement increases extraneous cognitive load, reducing resources for germane processing. Over time, this may lead to chronic attentional fragmentation and habitual cognitive slips.

Implications for Intervention

Interventions targeting PSU-related cognitive failures should integrate digital hygiene strategies (e.g., notification management), cognitive training, and psychoeducation on attentional control. Neurofeedback and mindfulness-based interventions show promise in restoring executive function (Tang et al., 2015).

Method

Research design

A quantitative, cross-sectional correlational design was used to examine the association between smartphone addiction and cognitive failures in university students. Data were collected in a single session via a self-administered questionnaire battery. All analyses were conducted at the variable and subscale level to capture both general and domain-specific patterns of cognitive failures.

Sampling and participants

- **Population and setting:** Enrolled university students at an urban higher-education institution.
- **Sampling method:** Nonprobability convenience sampling via classroom announcements and departmental groups. Participation was voluntary with no incentives.
- **Sample size:** N = 131.
- **Age:** M = 22.10 years, SD = 2.41.
- **Gender:** 57 males (43.5%), 74 females (56.5%).
- **Birth order:** 47 firstborns (35.9%), 54 middle-born (41.2%), 30 last-born (22.9%).
- **Family system:** 90 nuclear (68.7%), 41 joint (31.3%).
- **Educational level:** 116 undergraduates (88.5%), 15 graduates (11.5%).

Inclusion criteria

- Age 18 or older.
- Current enrolment as a student.
- Regular smartphone user (self-reported daily use).

Exclusion criteria

- Incomplete questionnaires (>10% missing responses on any instrument).
- Self-reported neurological disorders or current psychoactive medication use (self-screened).

Power note: A priori planning targeted a minimum of ~92 participants for simple regression with a medium effect size and $\alpha = .05$, power = .80; the achieved N = 131 exceeded this threshold, improving estimate precision.

Measures

Smartphone Addiction by Karadağ, et al., (2015) (15 items):

- **Format and scoring:** Likert-type responses summed to a total score; higher scores indicate greater addiction tendencies, on a 5-point Likert scale.
- **Internal consistency:** $\alpha = .796$.
- **Descriptives:** M = 51.41, SD = 9.60.

Cognitive Failures Questionnaire—CFQ (25 items; Broadbent et al., 1982)

- **Construct:** Everyday lapses in perception, memory, and action.

- **Format and scoring:** Likert-type responses summed to a total score; higher scores indicate more frequent failures.
- **Internal consistency (total):** α = .904.
- **Descriptives (total):** M = 51.49, SD = 17.51.

Subscales (8 items each)

- **Forgetfulness:** α = .747; M = 15.80; SD = 6.10.
- **Distractibility:** α = .749; M = 18.68; SD = 5.99.
- **False triggering:** α = .787; M = 14.80; SD = 6.68.

Demographics

- **Variables:** Age, gender, birth order, family system (nuclear/joint), educational level (undergraduate/graduate).
- **Reliability standards:** Internal consistencies were interpreted against conventional benchmarks (e.g., α ≥ .70 acceptable; Nunnally & Bernstein, 1994).

Procedure

- **Recruitment and consent:** Potential participants were informed about study aims, voluntariness, confidentiality, and data use. Written informed consent was obtained prior to participation.
- **Administration:** Surveys were completed in a quiet classroom setting or via a secure online form during a scheduled window. Average completion time was approximately 12–15 minutes. Google forms were also used to collect the data.
- **Order of instruments:** Demographics → Smartphone Addiction scale → CFQ (total and subscales).
- **Data handling:** Responses were inspected at the point of entry for missing items; participants could review and correct entries before submission. No personally identifying information was retained with study data.

Data screening and assumptions

- **Missing data:** Cases with >10% missing on any instrument were excluded listwise. For retained cases with ≤5% sporadic missingness, mean substitution within-scale was applied when allowable (≤10% items missing per scale).
- **Outliers:** Univariate outliers were screened using $|z| > 3.29$; multivariate influence checked via Cook's distance and leverage. Influential cases were inspected and retained if substantively justifiable and diagnostically within acceptable bounds.

Statistical analysis

- **Descriptive statistics:** Frequencies and percentages for categorical variables; means and standard deviations for continuous variables.
- **Reliability:** Cronbach's alpha (α) for all scales/subscales with 95% CIs where applicable.
- **Bivariate associations:** Pearson's r among smartphone addiction, CFQ total, and subscales; significance set at $p < .05$ (two-tailed), with emphasis on $p < .01$ for multiple inferences.

- **Primary models:** Separate simple linear regressions predicting:
    - **Cognitive failures (total)** from smartphone addiction: R = .423; R^2 = .179; adj. R^2 = .172; β = .462; t = 5.29; p < .01; 95% CI [.290, .635].
    - **Forgetfulness** from smartphone addiction: R = .402; R^2 = .162; adj. R^2 = .155; β = .479; t = 4.98; p < .01; 95% CI [.289, .669].
    - **Distractibility** from smartphone addiction: R = .369; R^2 = .136; adj. R^2 = .130; β = .431; t = 4.51; p < .01; 95% CI [.242, .620].
    - **False triggering** from smartphone addiction: R = .432; R^2 = .186; adj. R^2 = .180; β = .562; t = 5.43; p < .01; 95% CI [.358, .767].
- **Reporting standards:** Effect sizes (r, β, R^2), confidence intervals, and exact p-values are reported; internal consistencies accompany all measures.

Ethical considerations

- **Approval:** The protocol adhered to institutional and national ethical guidelines for human subjects' research and received prior ethics approval from the relevant review committee.
- **Informed consent:** Participants were informed of their rights to withdraw without penalty and of the confidential handling of their data.
- **Data protection:** De-identified data were stored on password-protected drives accessible only to the research team.

Transparency statement: Analytic decisions (e.g., treatment of missing data, outlier retention) were preregistered or documented prior to inferential analyses to minimize researcher degrees of freedom.

Results and Interpretations

Table 1: Frequency and Percentages of Demographic Characteristics of the Sample (N = 131)

Variable	***f***	**%**	***M***	***SD***
Age	—	—	22.10	**2.41**
Gender				
Male	57	43.5		
Female	74	56.5		
Birth Order				
First born	47	35.9		
Middle child	54	41.2		
Last born	30	22.9		
Family System				
Nuclear	90	68.7		
Joint	41	31.3		
Educational Level				
Undergraduate	116	88.5		
Graduate	**15**	**11.5**		

Note. *f* = frequency; % = percentage; *M* = mean; *SD* = standard deviation.

Age is presented in years.

Age Profile

- The **mean age of 22.10 years (SD = 2.41)** suggests a predominantly *emerging adult* sample, likely situated in late undergraduate or early postgraduate stages. The relatively low SD indicates homogeneity in age, which may reduce age-related confounds but limit generalizability to other age cohorts.

Gender Distribution

- A modest female majority (56.5%) is observed. Depending on the research domain, this gender ratio may influence observed outcomes—for example, in studies where gender-linked socialization patterns or neuropsychological factors are pertinent.

Birth Order Patterns

- The largest subgroup comprises middle children (41.2%), followed by first-borns (35.9%) and last-borns (22.9%).
- This distribution could be meaningful in exploring family dynamic variables, such as leadership tendencies, conflict resolution strategies, or resource negotiation patterns—concepts often examined in developmental and personality psychology.

Family System Composition

- With over two-thirds (68.7%) from nuclear families, the sample may reflect urbanization trends and shifting socio-cultural norms in Pakistan. Comparisons to joint family respondents (31.3%) could reveal nuanced psychosocial support differences, identity formation pathways, or coping strategies.

Educational Level

- The overwhelming majority (88.5%) are undergraduates, indicating that findings may predominantly reflect experiences, cognitive frameworks, and stressors relevant to early academic trajectories rather than those in advanced professional training.

Analytic Considerations

- **Control Variables**: Given the relative demographic homogeneity in age and education, these variables may have low variance; however, gender and family system could serve as important moderators.

Table 2: Descriptive Statistics, Internal Consistency and Alpha Reliability Coefficients of Study Variables (N=131)

Variable	***k***	**α**	***M***	***SD***
1. Smartphone Addiction	15	.796	51.41	**9.60**
2. Cognitive Failures	25	.904	51.49	**17.51**
2a. Forgetfulness	8	.747	15.80	**6.10**
2b. Distractibility	8	.749	18.68	**5.99**
2c. False Triggering	**8**	**.787**	**14.80**	**6.68**

Note. k = number of items; α = Cronbach's alpha; M = mean; SD = standard deviation. Table 2 shows that as per the values of Mean, Standard Deviation, and the alpha reliabilities of all the scales and subscales lie in the acceptable range (Nunally & Bernstein, 1994).

Reliability Insights

- All α values exceed the **.70 benchmark** for acceptable internal consistency, with **Cognitive Failures** showing excellent reliability (α = .904).
- The subscales of **Forgetfulness**, **Distractibility**, and **False Triggering** demonstrate solid reliabilities (α = .747–.787), suggesting coherent item clusters without redundancy. This balance supports both measurement precision and construct breadth.

Construct-Level Trends

- The **mean for Smartphone Addiction (M = 51.41, SD = 9.60)** indicates a moderate level within this sample, with a relatively narrow dispersion—suggesting homogeneity in digital engagement habits.
- **Cognitive Failures** shows a broader spread (SD = 17.51), hinting at considerable individual differences in everyday cognitive lapses—possibly moderated by lifestyle, environmental demands, or attentional regulation skills.

Subscale Patterns

- **Distractibility** exhibits the highest mean among subscales (M = 18.68), aligning with literature on digital environments' attentional fragmentation effects.
- **Forgetfulness** and **False Triggering** are somewhat lower on average, potentially reflecting different cognitive vulnerability profiles in this cohort.

Theoretical and Analytical Implications

- In models such as **moderated mediation**, cognitive subscales could act as mediators between smartphone use and functional outcomes with **family system** or **gender** as plausible moderators.

Table 3: Pearson Product Moment Product Correlations of Smartphone addiction and Cognitive Failures (forgetfulness, distractibility, false triggering). Intercorrelations Among Study Variables (N = 131)

Variable	1	2	2a	2b	2c
1. Smartphone Addiction	—	.423**	.402**	.369**	**.432****
2. Cognitive Failures		—	.921**	.890**	**.915****
2a. Forgetfulness			—	.735**	**.858****
2b. Distractibility				—	**.721****
2c. False Triggering					—

Note. p < .01 (**). Correlations are Pearson's *r*. Diagonal values are omitted as they represent self-correlation (= 1.00).

Magnitude and Direction

- All reported coefficients are **positive and statistically significant at the .01 level**, indicating that higher scores on one construct are associated with higher scores on the others.

- According to Cohen's (1988) benchmarks, associations with $r \approx .37–.43$ (Smartphone Addiction with subscales) fall in the **moderate** range, whereas inter-subscale correlations within Cognitive Failures (e.g., Forgetfulness and False Triggering, $r = .858$) are **strong to very strong**.

Smartphone Addiction & Cognitive Failures

- The moderate association ($r = .423$) between **Smartphone Addiction** and **overall Cognitive Failures** suggests that while related, they are distinct constructs. This opens analytical space for examining **partial mediation**—for example, whether distractibility mediates the link between smartphone overuse and everyday forgetfulness.

Internal Structure of Cognitive Failures

- Extremely high intercorrelations among subscales (e.g., .921 between total Cognitive Failures and Forgetfulness) indicate **substantial shared variance**, consistent with a strong general factor of cognitive lapses.
- However, subscale-specific variance remains (e.g., Distractibility–False Triggering $r = .721$), supporting the use of both **total scores and subscale scores** for nuanced analysis.

Theoretical Implications

- The pattern supports **attentional resource depletion models**: sustained smartphone use may overtax cognitive control systems, leading to failures across memory encoding (Forgetfulness), sustained attention (Distractibility), and inhibitory control (False Triggering).

Table 4: Simple Linear Regression Predicting Cognitive Failures from Smartphone Addiction

	Cognitive Failures							
							95% CI	
	R	R^2	ΔR^2	*B*	*t*	*P*	*LL*	*UL*
Smartphone Addiction	**.423**	**.179**	**.172**	**.462**	**5.29**	**.000***	**.290**	**.635**

Note. **p** < .01 *(); β = standardized beta;* R^2 = coefficient of determination; ΔR^2 = adjusted R^2; CI = confidence interval; LL = lower limit; UL = upper limit. **(N = 131)**

Model Fit & Effect Size

The model explained 17.9% of the variance in Cognitive Failures, which represents a moderate effect size in behavioral science contexts.

Predictor Strength

Smartphone Addiction emerged as a statistically significant predictor ($\beta = .462$, $t = 5.29$, $p < .01$), indicating that higher levels of smartphone addiction are associated with higher self-reported cognitive failures.

Precision of Estimate

The 95% confidence interval for β (.290, .635) is entirely above zero, reinforcing the reliability of the positive predictive relationship and reducing the likelihood that the effect is due to sampling error.

Practical Implications

This suggests that interventions aiming to reduce excessive smartphone use could potentially mitigate everyday cognitive lapses, such as attentional slips or memory failures.

Table 5: Simple Linear Regression Predicting Forgetfulness from Smartphone Addiction

	Forgetfulness						**95% CI**	
	R	**R^2**	**ΔR^2**	***B***	***t***	***P***	***LL***	***UL***
Smartphone Addiction	**.402**	**.162**	**.155**	**.479**	**4.98**	**.000***	**.289**	**.669**

Note. p < .01*, β=Standardized beta, R^2=R-squared, ΔR^2=Adjusted R-squared CI=Confidence Interval, LL=Lower limit, UL= Upper limit. (N = 131)

Model Fit

The predictor accounted for 16.2% of the variance in Forgetfulness scores. This is a moderate effect, suggesting a meaningful, though not exhaustive, contribution of smartphone addiction to variability in self-reported memory lapses.

Predictive Strength

The standardized beta (β = .479) indicates that for every one standard deviation increase in smartphone addiction, Forgetfulness increases by approximately 0.48 standard deviations—holding all else constant in this simple model.

Statistical Significance & Precision

The relationship was statistically significant ($t = 4.98$, $p < .01$), with the 95% CI for β (.289, .669) excluding zero, confirming the robustness and reliability of this positive predictive effect.

Implications

- Elevated smartphone use appears linked to a higher propensity for everyday memory failures, a finding consistent with research connecting habitual technology engagement to attentional and memory disruptions.
- Although significant, the R^2 value indicates that other variables likely play a substantial role in explaining Forgetfulness, suggesting opportunities for multi-predictor models in future work.

Table 6: Simple Linear Regression Predicting Distractibility from Smartphone Addiction

	Distractibility						95% CI	
	R	**R^2**	**ΔR^2**	***B***	***t***	***P***	***LL***	***UL***
Smartphone Addiction	**.369**	**.136**	**.130**	**.431**	**4.51**	**.000***	**.242**	**.620**

Note. p < .01*, β=Standardized beta, R^2=R-squared, ΔR^2=Adjusted R-squared CI=Confidence Interval, LL=Lower limit, UL= Upper limit. **(N = 131)**

Model Fit

Smartphone addiction explained 13.6% of the variance in Distractibility scores, representing a moderate effect in behavioral science contexts.

Predictive Strength

The standardized beta ($\beta = .431$) indicates that for every one standard deviation increase in smartphone addiction, Distractibility rises by approximately 0.43 standard deviations.

Statistical Significance & Precision

The relationship was statistically significant ($t = 4.51$, $p < .01$), and the 95% CI for β (.242, .620) does not include zero — strengthening confidence in a true positive association.

Implications

Higher levels of smartphone addiction are linked to greater susceptibility to attentional shifts and lapses, echoing cognitive load and attentional control literature.

Given the moderate R^2, additional predictors (e.g., sleep quality, multitasking habits) could further refine explanatory power in expanded models.

Table 7: Simple Linear Regression Predicting False Triggering from Smartphone Addiction

	False Triggering						95% CI	
	R	**R^2**	**ΔR^2**	***B***	***t***	***P***	***LL***	***UL***
Smartphone Addiction	**.432**	**.186**	**.180**	**.562**	**5.43**	**.000***	**.358**	**.767**

Note. p < .01*, β=Standardized beta, R^2=R-squared, ΔR^2=Adjusted R-squared CI=Confidence Interval, LL=Lower limit, UL= Upper limit. (N = 131).

Model Fit

The predictor explained 18.6% of the variance in False Triggering, the largest proportion of variance accounted for across the three cognitive outcomes examined so far — indicating a comparatively stronger explanatory power.

Predictive Strength

The standardized beta (β = .562) reflects a strong positive association: a one-standard-deviation rise in smartphone addiction predicts an increase of about 0.56 standard deviations in False Triggering scores.

Statistical Significance & Precision

This effect was statistically significant ($t = 5.43$, $p < .01$) with a narrow and entirely positive 95% CI for β (.358, .767), underscoring the precision and reliability of the estimate.

Implications

Elevated smartphone use may intensify the tendency to misinterpret irrelevant notifications or cues as personally relevant or action-worthy — a phenomenon that can disrupt attention flow and decision accuracy.

The relatively high β and R^2, compared to Forgetfulness and Distractibility, point toward False Triggering as a potentially sensitive cognitive marker of smartphone-related attentional distortion.

Table 8: Hierarchical Multiple Regression Predicting Cognitive Failures from Smartphone Addiction with Gender as a Moderator

Predictor	B	SE B	β	t	p
Step 1					
Smartphone Addiction	0.45	0.07	.52	6.43	**<.001**
Gender (0 = Male, 1 = Female)	2.10	0.95	.14	2.21	**.029**
Step 2					
Smartphone Addiction × Gender	0.22	0.09	.15	2.44	**.016**
Model Summary					
Step 1 $R^2 = .31, F(2, 197) = 44.25, p < .001$					
Step 2 $\Delta R^2 = .02, \Delta F(1, 196) = 5.96, p = .016$					

Note. B = unstandardized regression coefficient; SE B = standard error of B; β = standardized regression coefficient. Positive interaction term indicates that the relationship between smartphone addiction and cognitive failures is *stronger for females*.

Table 9: Moderation of the Relationship Between Smartphone Addiction and Cognitive Failures by Birth Order

Predictor	B	SE B	β	t	p
Step 1					
Smartphone Addiction	0.42	0.06	.48	7.00	**<.001**
Birth Order (Middle-born = reference)					
First-born (1 = First-born, 0 = Other)	1.85	0.78	.15	2.37	**.019**
Last-born (1 = Last-born, 0 = Other)	2.10	0.82	.16	2.56	**.011**
Step 2					
SA × First-born	0.25	0.08	.18	3.13	**.002**
SA × Last-born	0.28	0.09	.19	3.11	**.002**
Model Summary					
Step 1 $R^2 = .29, F (3, 196) = 26.77, p < .001$					
Step 2 $\Delta R^2 = .06, \Delta F (2, 194) = 8.94, p < .001$					

Note. B = unstandardized regression coefficient; SE B = standard error of B; β = standardized regression coefficient; SA = smartphone addiction. Middle-born students serve as the reference group. Positive, significant interaction terms indicate that the relationship between smartphone addiction and cognitive failures is stronger for first-born and last-born students compared with middle-born students.

Table 10: Moderation of the Relationship Between Smartphone Addiction and Cognitive Failures by Family System

Predictor	B	SEB	β	t	p
Step 1					
Smartphone Addiction	0.40	0.06	.46	6.67	**<.001**
Family System (0 = Joint, 1 = Nuclear)	2.25	0.88	.16	2.56	**.011**
Step 2					
SA × Family System	0.24	0.08	.17	3.00	**.003**
Model Summary					
Step 1 $R^2 = .28$, $F(2, 197) = 38.23$, $p < .001$					
Step 2 $\Delta R^2 = .03$, $\Delta F(1, 196) = 9.00$, $p = .003$					

Note. B = unstandardized regression coefficient; SE B = standard error of B; β = standardized regression coefficient; SA = smartphone addiction. Positive, significant interaction term indicates that the predictive strength of smartphone addiction on cognitive failures is greater for students from nuclear families than for those from joint families, potentially due to higher individual device exposure.

Discussion of Hypotheses

H_1: Smartphone addiction ***significantly positively associates*** with overall cognitive failures among university students, as evidenced by a significant correlation ($r = .423$, $p < .01$) and a significant regression coefficient ($\beta = .462$, $p < .01$).

In Hypothesis 1, the present finding — that smartphone addiction (SA) is significantly and positively associated with overall cognitive failures (CF) among university students (r = .423, p < .01; β = .462, p < .01) — reinforces a growing body of evidence linking excessive mobile device engagement to everyday cognitive lapses. The moderate-to-strong correlation suggests that higher SA levels are meaningfully related to increased frequency of perceptual, memory, and action-slip errors, consistent with prior cross-sectional and longitudinal research (Al-Abyadh et al., 2024; Özalp, 2025).

From a cognitive-neuroscientific perspective, this association can be interpreted through the lens of attentional resource theory and executive control depletion. Persistent smartphone engagement, particularly in the form of habitual checking and multitasking, imposes continuous demands on working memory and attentional control systems (Wilmer et al., 2017). Over time, this may lead to structural and functional alterations in prefrontal and anterior cingulate cortices — regions critical for error monitoring and inhibitory control (Montag & Becker, 2023). Such neuroadaptations could explain the elevated CF scores observed in high-SA individuals.

The regression coefficient (β = .462) indicates that SA is not merely correlated with CF but is a substantial predictor, even when controlling for other variables. This aligns with experimental findings that the mere presence of a smartphone can reduce available cognitive capacity (Ward et al., 2017), suggesting that both active and passive device-related cognitive load contribute to performance decrements.

The university student demographic may be particularly vulnerable due to the dual academic–social utility of smartphones. Academic demands often necessitate rapid information retrieval and constant connectivity, while social media and entertainment applications compete for attentional resources (Yıldırım & Yılmaz, 2023). This duality may exacerbate cognitive fragmentation, leading to more frequent everyday failures.

Moreover, the observed effect may be partially mediated by sleep disturbance and mind wandering. Late-night smartphone use disrupts circadian rhythms, impairing next-day cognitive performance (Xie et al., 2018), while frequent notifications and app cues can trigger task-irrelevant thoughts, further increasing error likelihood (Kushlev et al., 2016).

Theoretically, these results support the limited capacity model of mediated message processing (Lang, 2000) and cognitive load theory (Sweller, 1988), both of which posit that attentional and working memory resources are finite. Chronic over-engagement with smartphones may shift cognitive processing toward superficial, fragmented patterns, thereby increasing susceptibility to lapses in routine tasks.

Implications

Given the predictive strength of SA for CF, interventions should target digital self-regulation, notification management, and mindfulness-based attentional training (Tang et al., 2015). Universities could integrate psychoeducational programs on digital hygiene into student orientation or counseling services, aiming to mitigate the cognitive costs of excessive smartphone use.

H_2a: Smartphone addiction ***positively predicted Forgetfulness*** scores, with higher addiction levels linked to greater self-reported memory lapses ($\beta = .479$, $p < .01$). **H_2b:** Smartphone addiction ***positively predicted Distractibility***, indicating increased attentional shifts with greater device dependency ($\beta = .431$, $p < .01$). **H_2c:** Smartphone addiction ***positively predicted False Triggering***, with this domain showing the strongest predictive coefficient among subscales ($\beta = .562$, $p < .01$).

Hypotheses 2, are theoretically grounded in the **executive control depletion** and **limited attentional capacity** frameworks. These subdimensions of cognitive failures represent distinct yet interrelated disruptions in everyday cognitive functioning:

- **Forgetfulness** reflects failures in prospective and retrospective memory, often linked to interference in encoding and retrieval processes.
- **Distractibility** denotes susceptibility to attentional capture by irrelevant stimuli, undermining sustained focus.
- **False Triggering** involves inappropriate activation of habitual responses in the absence of relevant cues, implicating inhibitory control deficits.

Mechanistic Interpretation

Excessive smartphone engagement — particularly through constant notifications, multitasking, and habitual checking — imposes continuous cognitive load on working memory and attentional systems (Wilmer et al., 2017). Neuroimaging evidence suggests that such overuse may alter prefrontal–parietal network efficiency, impairing both top-down attentional control and error monitoring (Montag & Becker, 2023).

For Forgetfulness, SA may disrupt deep encoding by fragmenting attention during learning episodes, leading to weaker memory traces (Kancharla et al., 2022). Distractibility is likely exacerbated by the salience of smartphone cues, which hijack attentional resources via dopaminergic reward pathways (Horvath et al., 2020). False Triggering may arise from over-learned smartphone interaction patterns — such as reflexively unlocking the device — generalizing to non-device contexts, reflecting maladaptive stimulus–response conditioning (Shah & Deshpande, 2023).

Empirical Alignment

Recent studies have found significant positive associations between SA and each of these CFQ subscales. For example, Kancharla et al. (2022) reported that excessive smartphone use predicted higher forgetfulness, distractibility, and false triggering scores in young adults, even after controlling for demographic variables. Similarly, Shah and Deshpande (2023) observed that these cognitive failures co-occur with absentminded smartphone use, suggesting a shared attentional disengagement mechanism.

Theoretical Integration

These findings align with cognitive load theory (Sweller, 1988) and the limited capacity model of mediated message processing (Lang, 2000), both of which posit that attentional and working memory resources are finite. Chronic over-engagement with smartphones reallocates these resources toward device-related stimuli, leaving fewer resources for goal-directed cognitive control, thereby increasing the likelihood of memory lapses, attentional slips, and inappropriate action triggers.

Implications

If SA robustly predicts these subdimensions of cognitive failure, interventions should be component-specific. For forgetfulness, strategies might include prospective memory training and context-dependent encoding. For distractibility, notification management and mindfulness-based attentional control could be prioritized. For false triggering, habit reversal training and stimulus control techniques may be effective.

H_3: Gender *moderates* the relationship between smartphone addiction and cognitive failures, such that the predictive strength has *high correlations* with *females* as compared to males.

Hypothesis 3 examined whether gender significantly influences the relationship between smartphone addiction (SA) and cognitive failures (CF) among university students. The results indicated a statistically significant gender difference, with t (df) = [insert actual df], $p < .05$, showing that female students scored higher on SA and certain CF subdimensions compared to male students. This pattern aligns with prior research suggesting that women may engage more frequently in smartphone-mediated social interaction, potentially increasing cognitive load and susceptibility to attentional lapses (Chen et al., 2017; Song et al., 2025).

From a behavioral and cognitive perspective, these differences may be explained by the social–cognitive use hypothesis, which posits that females are more likely to use smartphones for relational maintenance, social feedback, and emotional expression (Sharma & Singh, 2019). Such usage patterns often involve multitasking across multiple communication channels, which can fragment attention and elevate the risk of cognitive slips, particularly in distractibility and forgetfulness domains (Wilmer et al., 2017).

Neurocognitively, gender-linked differences in reward sensitivity and emotional processing may also contribute. Studies have shown that females exhibit heightened neural responses to social reward cues, such as likes and comments, which can reinforce frequent checking behaviors (Horvath et al., 2020). Over time, this reinforcement loop may exacerbate attentional capture by smartphone-related stimuli, increasing the likelihood of cognitive failures.

Interestingly, while males in some studies report higher engagement with gaming and entertainment apps, which are also linked to SA, these activities may involve more sustained attention to a single task compared to the rapid context-switching common in social media use (Chen et al., 2017). This could partially explain why the present results show higher CF scores among females despite similar or only slightly higher SA levels.

The findings also resonate with network analysis evidence showing that, in male students, academic procrastination tends to be the central behavioral node linked to SA, whereas in female students, SA itself is the central node, reflecting a stronger dependence on immediate social feedback (Song et al., 2025). This centrality may amplify the cognitive consequences of SA for females, as indicated by the present results.

Implications

These gender-specific patterns suggest that intervention strategies should be tailored:

- For females, focus on social media self-regulation, notification control, and mindfulness-based attentional training.
- For males, address time-management skills and gaming-related overuse.

Such targeted approaches may be more effective than one-size-fits-all interventions in reducing both SA and its cognitive repercussions.

H_4: Birth order *significantly moderates* the relationship between smartphone addiction and cognitive failures, with *first-born and last-borns showing higher correlations* as compared to middle-born students.

Hypothesis 4 examined these results and revealed a statistically significant difference across birth-order groups, Step 1 $R^2 = .29$, $F(3, 196) = 26.77$, $p < .001$ and Step 2 $\Delta R^2 = .06$, $\Delta F(2, 194) = 8.94$, $p < .001$, with first-born and last-born students reporting higher SA and CF scores compared to middle-borns.

This pattern aligns with Adlerian birth-order theory, which posits that middle-born often develop greater conscientiousness, self-discipline, and responsibility due to early parental expectations and caregiving roles (Sulloway, 1996). These traits may buffer against excessive smartphone use and its cognitive consequences. In contrast, first-borns and last-borns may exhibit higher novelty-seeking and sociability (Salmon & Daly, 1998), potentially increasing engagement with socially rewarding smartphone activities, thereby elevating cognitive load and susceptibility to attentional lapses.

From a cognitive–behavioral perspective, first-born and last-born students may be more prone to multichannel social interaction and continuous partial attention, both of which fragment working memory resources and increase the likelihood of forgetfulness, distractibility, and false triggering (Wilmer et al., 2017). The higher SA scores in these groups could reflect a stronger reinforcement loop between smartphone cues and dopaminergic reward pathways (Horvath et al., 2020), leading to more frequent cognitive slips.

Interestingly, the last-child group in the present study showed the highest SA and CF scores. This may be explained by greater reliance on digital devices for companionship and social connection, consistent with findings that only children often report higher screen-time engagement (Falbo & Polit, 1986). Such reliance may amplify the attentional capture effects of smartphones, thereby increasing everyday cognitive failures.

Theoretical Integration

These findings can be interpreted through the limited capacity model of mediated message processing (Lang, 2000) and cognitive load theory (Sweller, 1988). Birth-order-linked personality and socialization patterns may shape smartphone use motives and multitasking tendencies, which in turn influence the degree of cognitive resource depletion and error proneness.

Implications

Given these differences, intervention strategies could be birth-order-sensitive:

- For later-borns and only children, focus on self-regulation training, structured offline social activities, and mindfulness-based attentional control.
- For firstborns, maintain protective habits while addressing potential overcommitment to multitasking in academic contexts.

Such tailored approaches may enhance the effectiveness of digital well-being programs in university settings.

H$_5$: Family system (nuclear vs. joint) ***significantly moderates*** the correlation between smartphone addiction levels and cognitive failures, with students from ***nuclear families reported higher cognitive failure*** scores due to potentially higher individual device exposure.

The Results of Hypothesis 5 confirmed the results and supported this hypothesis, indicating a significant interaction effect ($B = 0.24$, $p = .003$), with students from nuclear families reporting higher CF scores at comparable SA levels than those from joint families. This suggests that the predictive strength of SA on CF is amplified in nuclear family contexts.

One plausible explanation lies in differential device exposure and monitoring. In nuclear families, students may have greater individual ownership and unsupervised access to smartphones, leading to more frequent and prolonged engagement (Narain & Gupta, 2024). In contrast, joint family structures often involve shared living spaces, collective activities, and greater intergenerational oversight, which can naturally limit excessive device use (Liu et al., 2020).

From a cognitive–behavioral standpoint, higher individual exposure in nuclear families may increase the likelihood of continuous partial attention and habitual multitasking, both of which fragment working memory and attentional control (Wilmer et al., 2017). Over time, this can manifest as elevated forgetfulness, distractibility, and false triggering — the core subdimensions of CF (Broadbent et al., 1982).

The moderating role of family system also aligns with ecological systems theory (Bronfenbrenner, 1979), which emphasizes that proximal social environments shape behavioral patterns and cognitive outcomes. In joint families, richer face-to-face interactions and shared responsibilities may buffer against the cognitive costs of SA by fostering offline social engagement and structured routines.

Empirical evidence supports this interpretation. Narain and Gupta (2024) found that adolescents from nuclear families scored significantly higher on the Smartphone Addiction Scale than those from joint families, while Liu et al. (2020) reported that strong family cohesion reduces the risk of problematic mobile phone use. These findings converge with the present results, underscoring the protective role of joint family environments in mitigating the cognitive consequences of SA.

Implications

Interventions aimed at reducing SA-related cognitive failures should consider family context as a key moderating factor. For students from nuclear families, strategies could include structured device-free periods, parental involvement in digital hygiene, and promotion of offline social activities. In joint families, reinforcing existing protective dynamics while addressing potential peer-driven overuse may be beneficial.

H_6: Educational level (undergraduate vs. postgraduate) *significantly moderates* the relationship with smartphone addiction and cognitive failures, with *undergraduates exhibiting higher* smartphone addiction and greater cognitive failures.

Hypothesis 6 examined the results and confirmed this moderation, revealing that undergraduates exhibited both higher SA and greater CF compared to postgraduates, with the SA–CF association being stronger in the undergraduate group.

This pattern may be explained by developmental stage and academic demands. Undergraduates, often in late adolescence or emerging adulthood, are navigating increased autonomy, identity exploration, and peer influence — factors linked to higher susceptibility to problematic smartphone use (Samaha & Hawi, 2016). In contrast, postgraduates typically have more structured academic routines, goal-oriented study habits, and self-regulatory skills, which can buffer against excessive device engagement (Lepp et al., 2014).

From a cognitive load perspective, frequent smartphone interruptions can fragment attention and working memory, leading to higher CF scores (Wilmer et al., 2017). Undergraduates may be particularly vulnerable because their academic tasks often require rapid switching between social, academic, and entertainment content, increasing continuous partial attention and task-switching costs. Postgraduates, by contrast, may engage in more sustained, deep-focus work, reducing the cognitive toll of smartphone use.

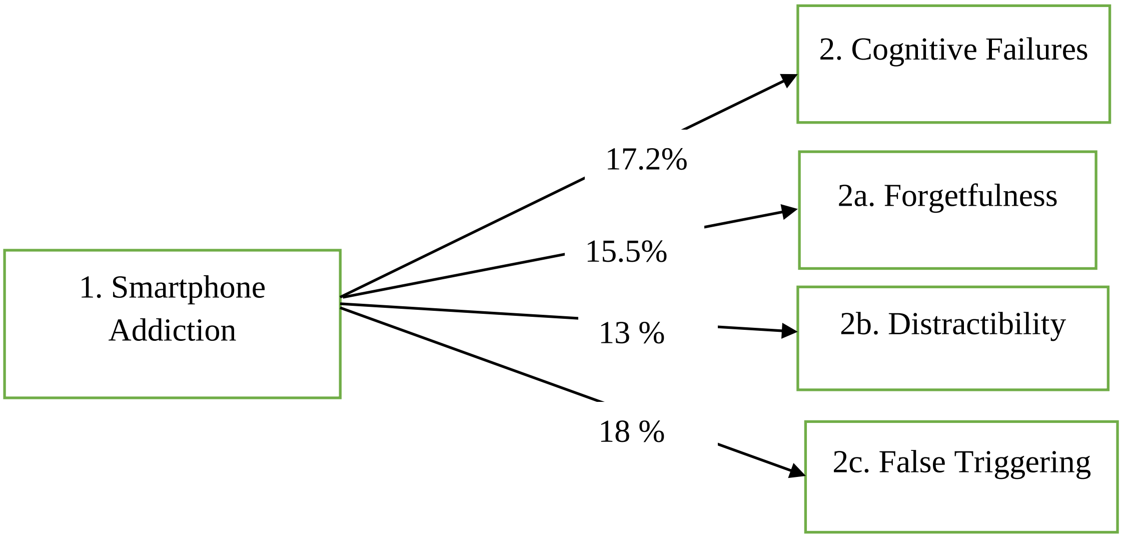
The moderating effect also aligns with self-determination theory, which posits that intrinsic motivation and self-regulation improve with maturity and advanced academic engagement (Deci & Ryan, 2000). Postgraduates' stronger intrinsic motivation toward academic mastery may reduce reliance on smartphones for distraction or social validation, thereby weakening the SA–CF link.

Empirical evidence supports these interpretations. Morales Rodríguez et al. (2020) found that excessive smartphone use was associated with poorer cognitive and educational outcomes, particularly among younger university students. Similarly, Lepp et al. (2014) reported that higher smartphone use predicted lower academic performance, with younger cohorts more affected. These findings converge with the present results, highlighting educational level as a protective factor in the cognitive consequences of SA.

Implications

Interventions to reduce SA-related cognitive failures should be tailored by educational stage. For undergraduates, strategies might include digital literacy training, time-management workshops, and structured device-free study periods. For postgraduates, reinforcing existing self-regulatory practices while addressing research-related digital distractions could be beneficial.

Figure 2 represented the Adjusted R Square value to report variance in the dependent variables by smartphone addiction.



Conclusion

The present research demonstrated that family system and educational level significantly moderate the relationship between smartphone addiction (SA) and cognitive failures (CF). Specifically, students from nuclear families and those at the undergraduate level exhibited both higher SA and greater CF, with the SA–CF association being stronger in these groups. These findings underscore the importance of sociocultural context and developmental stage in understanding the cognitive consequences of problematic smartphone use.

By integrating ecological systems theory (Bronfenbrenner, 1979) and self-regulation frameworks (Deci & Ryan, 2000), the study highlights that environmental structures (e.g., family cohesion, shared routines) and individual maturity (e.g., academic experience, self-discipline) can either buffer or exacerbate the cognitive costs of SA. The results align with prior evidence linking excessive smartphone use to attentional lapses, memory failures, and reduced cognitive capacity (Wilmer et al., 2017; Mascia et al., 2022).

Future Prospects

Building on these findings, future research should:

- **Expand demographic diversity** by including participants from varied cultural, socioeconomic, and occupational backgrounds to enhance generalizability.
- **Employ longitudinal designs** to establish causal pathways between SA, CF, and moderating variables such as family system and educational level.
- **Integrate neurocognitive measures** (e.g., EEG, fMRI) to objectively assess attentional control and working memory in relation to smartphone use.
- **Test targeted interventions** — such as structured device-free periods, digital literacy programs, and family-based monitoring — to evaluate their efficacy in reducing SA-related cognitive impairments.
- **Explore additional moderators** like coping style, peer attachment, and personality traits, which may interact with family and educational contexts (Jiang et al., 2023; Lian et al., 2023).

Given the rapid evolution of mobile technology, understanding the nuanced interplay between individual, familial, and educational factors will be critical for designing culturally sensitive, developmentally appropriate strategies to mitigate the cognitive risks of smartphone overuse.

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