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Problematic social media use and cognitive performance in young adults: Associations with selective attention and inhibitory control

CONCHITA SISÍ[1,2*], STÅLE PALLESEN[3,4] and M.P. FERNÁNDEZ-MARTÍN[1]

[1] Department of Psychology, HM Faculty of Health Sciences, Camilo José Cela University, 28692, Madrid, Spain

[2] Department of Psychology, Faculty of Health Sciences, Unie University, 28029, Madrid, Spain

[3] Department of Psychosocial Science, University of Bergen, 5015, Bergen, Norway

[4] Norwegian Competence Center for Gambling and Gaming Reseach Research, University of Bergen, 5020, Bergen, Norway

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ABSTRACT

Background and Aims: Problematic social media use (PSMU) has been associated with emotional and behavioral difficulties, yet its relationship with cognitive performance remains insufficiently understood. This study examined whether PSMU is associated with deficits in selective attention and inhibitory control, and whether sex moderates these associations. *Methods:* A total of 943 Spanish young adults (18–35 years) completed the Bergen Social Media Addiction Scale (BSMAS) and two computerized tasks: the Stroop task, assessing selective attention, and the Simon task, assessing inhibitory control. Correlational and multiple regression analyses examined associations between PSMU severity, cognitive performance, age, and daily social media time of use. Moderation analyses examined sex differences. *Results:* PSMU showed a positive correlation with Stroop reaction times ($r = .65$, $p < .05$), indicating a positive relationship between attentional interference and PSMU scores. However, in regression models, greater daily social media time of use, rather than PSMU severity, was the only significant correlate of slower Stroop performance ($\beta = .28$, $p < .001$). No significant associations were found between PSMU and Simon task performance. A significant Sex × PSMU interaction ($\beta = .14$, $p = .018$) indicated that the association between PSMU and slower Stroop performance was stronger among women than among men. *Discussion and Conclusions:* Selective attention appeared to be more closely associated with daily social media time of use than inhibitory control. Our findings underscore the need to distinguish between problematic use and overall time of use when assessing cognitive correlates.

KEYWORDS

problematic social media use, selective attention, inhibitory control, sex differences, young adults

INTRODUCTION

Recent data indicate that close to 90% of young adults in Spain use social media regularly, often for multiple hours (We Are Social & Meltwater, 2024). Although these platforms foster communication, creativity, and social connections, problematic social media use (PSMU) has been associated with adverse outcomes, including emotional, behavioral, and cognitive difficulties (Allcott, Braghieri, Eichmeyer, & Gentzkow, 2020; Auxier & Anderson, 2021; Andreassen et al., 2016; Duradoni, Innocenti, & Guazzini, 2020).

Despite increasing scholarly attention (Cheng, Lau, Chan, & Luk, 2021), social media addiction is not recognized in current psychiatric nosology (DSM-5; American Psychiatric

*Corresponding author.
E-mail: conchitasisimartin@gmail.com

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Association, 2013; ICD-11 World Health Organization, 2022). Therefore, we use the term PSMU while acknowledging ongoing debates regarding the use of addiction-related terminology in this field and its current lack of formal classification (e.g., Demetrovics et al., 2026). PSMU is typically used to describe patterns of problematic or maladaptive engagement despite negative consequences (Bányai et al., 2017), although its conceptualization remains under discussion. It is frequently conceptualized in line with Griffiths' (2022) framework of behavioral addictions, emphasizing symptoms such as salience, mood modification, tolerance, withdrawal, conflict, and relapse, with empirical evidence linking PSMU to emotional dysregulation, sleep disturbances, and cognitive impairments (Montag, Wegmann, Sariyska, Demetrovics, & Brand, 2021). At the same time, this conceptualization has been subject to criticism and may not be fully aligned with current diagnostic frameworks such as the ICD-11, highlighting the need for further conceptual refinement (Demetrovics et al., 2026). However, the relationship between PSMU and cognitive functioning remains insufficiently explored (Arness & Ollis, 2023).

The hyper-stimulating design of social media, constant connectivity, notifications, and algorithmic reward cycles, may disrupt executive functions (Liu, Liu, Kendrick, Montag, & Becker, 2024). Emerging neuroscientific evidence further supports this link, showing that alterations in large-scale brain networks involved in cognitive control may predict the severity of problematic social media use in youth (Park, Lacadie, Zhao, & Potenza, 2026). Platform features such as persistent notifications may overload attentional systems and promote reward-driven behavior (Farchakh et al., 2022). This is particularly concerning for young adults, whose attentional systems are still maturing (Berryman, Ferguson, & Negy, 2018; Wilson, Fornasier, & White, 2010).

Current evidence suggests that selective attention and inhibitory control are especially affected in individuals with PSMU (Cheng et al., 2021; Montag et al., 2024). Attention is essential for filtering and responding to environmental stimuli, with impairments linked to poorer academic and psychological outcomes (Barry et al., 2002). Many prior studies have relied on subjective measures of cognitive functioning, which may be prone to bias, highlighting the need for objective measures and experimental paradigms (Wegmann, Müller, Turel, & Brand, 2020). From a theoretical perspective, dual-process and executive control frameworks suggest that repeated engagement with highly rewarding stimuli may bias attentional systems toward salient cues while weakening top-down inhibitory control (Brand et al., 2019; Montag et al., 2021; Wegmann et al., 2020). In the context of PSMU, this may translate into difficulties disengaging from social media-related stimuli and regulating impulsive responses. Importantly, some studies have gone beyond usage time and examined cognitive performance in relation to problematic use, which is relevant because time spent on social media may capture exposure, whereas PSMU reflects dysregulated engagement and impaired control. These studies have reported alterations in inhibitory control and executive functioning (e.g., Gao, Jia, Zhao, & Zhang, 2019; Müller et al., 2025; Reed, 2023).

Selective attention, the ability to suppress irrelevant stimuli, appears particularly sensitive to PSMU. Research shows diminished performance on selective attention tasks among individuals with high levels of social media use (Cain, Leonard, Gabrieli, & Finn, 2016; Chen, Li, Guo, & Wang, 2023), though these studies operationalized use merely as time spent online. Importantly, time spent on social media represents a related but distinct construct, which may capture exposure rather than maladaptive patterns of use. Distinguishing between duration and problematic engagement is therefore critical when examining cognitive outcomes. Cognitive interference effects, such as those seen in the Stroop task (Stroop, 1935), further demonstrate inhibitory deficits in individuals with PSMU (Scarpina & Tagini, 2017; Macleod, 1992; Wegmann et al., 2020).

Inhibitory control, reflecting suppression of automatic responses, is central to executive functioning and highly relevant to PSMU, as affected individuals have been shown to struggle to resist notifications and impulsive platform engagement (Montag et al., 2024). Performance deficits also appear in tasks such as the Simon task (Simon, 1967), where individuals with higher levels of PSMU show slower responses and reduced accuracy than the comparison group (Wegmann et al., 2020; Kuss & Griffiths, 2017). Still, most scholars operationalize PSMU in terms of time spent online or via ad hoc screening questions. Only a few studies have utilized validated measures such as the Bergen Social Media Addiction Scale (BSMAS) in relation to cognitive performance (Aydin et al., 2020; Montag & Markett, 2023). This constitutes a critical gap, as greater usage duration does not necessarily reflect maladaptive, compulsive engagement. Regarding sex differences, research remains inconclusive. Although some studies note higher PSMU symptoms among young women and slightly stronger inhibitory control among young men (Wang, Wang, Qi, Liu, & Guo, 2025), as well as sex-moderated effects from related fields (Todorovic et al., 2025), no consistent interaction between sex and PSMU on cognition has yet been established, evidencing the need for further empirical clarification (Patel, Bhagat, & Dixit, 2024).

Taken together, these findings highlight the need for studies that integrate theoretically grounded measures of PSMU with objective cognitive tasks, while accounting for the role of usage duration. Accordingly, distinguishing between usage duration and problematic engagement represents a key aspect of the present study. Against this backdrop, the present study examines whether individuals with higher PSMU show deficits in selective attention and inhibitory control, whether these outcomes differ by sex, and whether specific PSMU dimensions, particularly loss of control, are especially associated with cognitive impairments. The hypotheses, derived from previous studies on the field, are as follows: H1: Higher PSMU severity (BSMAS total score) will be associated with poorer performance on attention and inhibitory-control tasks, as reflected in longer reaction times and lower accuracy in the Stroop and Simon tasks (Ioannidis, Hook, Wickham, Grant, & Chamberlain, 2019; Zhang et al., 2023). H2: The association between PSMU severity and cognitive performance will remain significant after controlling for age and total daily time spent on social media (Reed, 2023; Varchetta et al., 2024; Yajie, Xin, Xiangchun, & Liping, 2022). H3: The "loss of control" items of the BSMAS (items 2, 4, and 5) will be associated with reaction time and accuracy in the Stroop and Simon tasks, beyond the effects of the remaining BSMAS items and self-reported time spent on social media. H4: Sex will moderate the relationship between PSMU severity and cognitive performance, such that negative associations between PSMU and attention/inhibitory control will be stronger in females than in males (Varchetta et al., 2024).

In this study, we examine two key cognitive variables: selective attention, the ability to focus on relevant stimuli while filtering out distractions, and inhibitory control, the capacity to suppress automatic responses in favor of goal-directed behavior.

METHODS

Participants

A sample of young adults aged 18–35 years from Spain was recruited for the study. An a priori power analysis was conducted using G*Power (Faul, Erdfelder, & Albert-Georg, 2007) for a moderated multiple regression model, focusing on the interaction between BSMAS and sex as a single tested predictor. The analysis assumed an alpha level of .05, statistical power of .80, and a small effect size (f^2 = .02). Under these parameters, the minimum required sample size was 395 participants. The final sample consisted of 943 participants. Participants were recruited through the online platform *Prolific*, which was chosen due to its ability to implement pre-screening filters, ensuring that participants met the specific inclusion criteria. The platform also facilitates efficient payment processing and communication with participants. The study was conducted fully online. Participants completed the survey and cognitive tasks remotely using their own devices, without direct supervision. Further details on participant's pre-screening are provided under the *Procedure section*. Data collection was fully funded by Vice-Rectorate for Research, Science, and Doctoral Studies of Camilo José Cela University through a grant of 5.000€ *(See Section Funding).* Data collection lasted for a total of 14 days, including a pilot testing phase. Participants had a mean age of 26.6 years (SD = 4.3), and age was normally distributed. 52.4% of the participants were male. The majority (76.6%) had a university-level education. Daily social media time varied: the largest group (43.9%) reported 1–3 h of daily use, with smaller proportions reporting <30 min (3.6%) or >5 h (11.5%). The mean score on the BSMAS was 15.91 (SD = 4.68).

Measures

Socio-demographic data: Variables commonly linked to social media use were assessed (Sheldon & Bryant, 2016; Yudes, Rey, & Extremera, 2021), including age, sex, educational level (currently studying vs. not; high school, university, master's, or doctorate), marital status, diagnosed mental disorders, social media use for work, nationality, primary language, and daily social media time of use (0–30 min, 30 min–1 hour, 1–3 h, 3–5 h, or more than 5 h). Table 1 presents the socio-demographic data of the sample.

Bergen Social Media Addiction Scale (BSMAS) (Andreassen et al., 2016): This scale was used to assess PSMU levels among participants. While the BSMAS is widely used, it is based on self-report and does not rely on clinical diagnosis, which should be considered when interpreting findings. The BSMAS consists of six items rated on a 5-point Likert scale, ranging from "very rarely" (1) to "very often" (5). It evaluates core addiction criteria such as salience, mood modification, tolerance, withdrawal, conflict, and relapse. The scale has demonstrated good reliability (α= .85) and validity in Spanish-speaking populations (Sisí, Pallesen, & Fernández-Martín, 2025). For the current study, an α = .79 was obtained. For the purposes of the present study, both the total BSMAS score and specific item groupings were used. In particular, items 2, 4, and 5 were considered to reflect "loss of control," while items 1, 3, and 6 were analyzed as a complementary dimension.

Computerized version of the "Stroop Task" (Stroop, 1935) comprised a computerized version adapted from Afsaneh et al. (2012). Internal consistency for reaction times (RTs) was estimated using a split-half reliability approach with Spearman–Brown correction, following recommendations for continuous response-time data (Hedge, Powell, & Sumner, 2018), where ρ represents the Spearman–Brown corrected reliability coefficient. Trials with incorrect responses or RTs below 200 ms or above 3 SDs from the participant's mean were excluded. For the Stroop task, reliability was ρ congruent = .86, ρ incongruent = .82, and ρ interference = .78. This task was used to assess selective attention. Participants were presented with color words displayed in incongruent ink colors (e.g., the word "red"

Table 1. Socio-demographic characteristics of the sample (N = 943)

		N	%
Sex	Male	494	52.4%
	Female	449	47.6%
Educational Level	Mandatory School	46	4.9%
	Baccalaureate	116	12.3%
	University (Bachelors, Masters)	722	76.6%
	PhD	59	6.3%
Social media daily time of use (hours)	0–30 min	34	3.6%
	30–60 min	124	13.1%
	1–3 h	414	43.9%
	3–5 h	263	27.9%
	>5 h	108	11.5%

displayed in blue ink) and were required to identify the ink color while ignoring the word meaning by clicking on the correct color name choosing from a list of 4 possible colors displayed. Reaction times and error rates were recorded, with longer reaction times and higher error rates on incongruent trials indicating greater interference. The task was administered using Python and Streamlit to create an interactive interface. Stimuli were dynamically generated to include 20 trials, balanced between congruent (color matches the word) and incongruent (color does not match the word) conditions. Instructions were displayed to guide participants through the test. A button interface was used to record responses as "Correct" or "Incorrect," along with reaction times. *See Appendix 1 for the Python Code for the tasks.* Longer response times indicate worse performance on the task, reflecting greater attentional interference. Measures regarding the Stroop task included: average response time, total correct answers and total incorrect answers.

Computerized version of the Simon Task: (Simon, 1967). A short version by Cevada et al. (2019) was adapted to a computerized format. Internal consistency for reaction times (RTs) was estimated with the same procedure as for the Stroop task (Hedge et al., 2018). Trials with incorrect responses or RTs below 200 ms or above 3 SDs from the participant's mean were excluded. For the Simon task, reliability was $\rho\_congruent = .84$, $\rho\_incongruent = .81$, and $\rho\_interference = .76$. This task assesses primarily inhibitory control. Participants responded to the color of a stimulus appearing on either side of the screen, with congruent trials where stimuli appear on the same side as the response key and incongruent trials where stimuli appear on the opposite side. Reaction times and accuracy were analyzed to evaluate attentional performance. A colored circle (red or green) was displayed on the left or right side of the screen. Participants were instructed to ignore the position of the circle and respond solely based on its color: red required a right-button press, whereas green required a left-button press. The test included congruent and incongruent trials to measure response times and accuracy. The task was implemented using Python and Streamlit for dynamic stimulus presentation and response recording. Each trial was presented with a single stimulus displayed at a random position, balanced between congruent and incongruent conditions. Measures regarding the task included: the mean reaction times (RTs) for all trials, and the interference score (RT_incongruent − RT_congruent), later referred to as "accuracy". Larger interference values indicate poorer inhibitory control (i.e., greater slowing on incongruent trials). The test, including the code used to implement the Stroop and Simon tasks, is attached as an appendix. This code was written in Python using Streamlit and includes detailed comments for reproducibility and further exploration.

Procedure

This study followed a cross-sectional correlational design. An initial pilot test was conducted with 25 participants. These participants provided feedback on the testing and survey procedures, reporting issues such as technical difficulties and ambiguities in the instructions. Based on this feedback, adjustments were made to the instructions to improve clarity, and the average completion time for the tasks was re-estimated. The updated survey- and test protocol was then used for the main study.

Eligibility criteria comprised: having Spanish as primary language and to hold a Spanish nationality. These criteria were deemed necessary for the administration of the BSMAS, which is validated for use in Spanish-speaking populations (Sisí, Pallesen, & Fernández-Martín, 2025). Participants were excluded if they reported needing social media for professional purposes, had a diagnosed mental illness, or had a physical medical condition known to affect attention (two specific ad hoc questions for this matter were included: "*Do you use social media platforms (e.g., Instagram, TikTok, LinkedIn, X/Twitter, Facebook) as part of your professional duties or to manage your business activities, "Have you ever been diagnosed by a healthcare professional with any mental or neurological condition that could affect attention or mood (e.g., ADHD, depression, anxiety, epilepsy, traumatic brain injury)?").* This ensured the validity of the attention measures and reduced potential confounding factors. All participants were required to have at least 10 prior submissions in *Prolific*, with a minimum of 90% approval rate from earlier participation, to ensure they were familiar with the platform as well as to strengthen the quality of the submissions.

Recruitment was completed within two weeks, including the pilot testing phase and re-adjusting after pilot testing. On average, participants completed the survey/testing in 19 min. Participants were compensated at a rate of £ 7.12/hour, in line with Prolific's recommended rates at the time of data collection. Compensation rates adhered to *Prolific's* guidelines to ensure ethical remuneration.

Statistical analysis

Initially, descriptive analyses were used to summarize the main sociodemographic and key study variables. Spearman correlations were used to examine bivariate associations as reaction-time variables showed skewed distributions. For hypothesis testing (H2–H4), linear regression models were employed, as these models are robust to deviations from normality with large sample sizes ($N = 943$). Residuals were inspected to ensure that no severe violations of model assumptions were present. Correlation coefficients were interpreted according to Cohen's (1988) conventional thresholds, where values of .10, .30, and .50 correspond to small, medium, and large effect sizes, respectively. Additionally, linear regression analyses were conducted to explore the Stroop variable, given its previously observed associations with both BSMAS scores and daily social media time of use. Preliminary analyses were conducted to ensure no violations regarding normality, linearity, multicollinearity and homoscedasticity. All statistical analyses were performed using IBM SPSS Statistics (version 25.0), with a two-tailed significance threshold set at $p < .05$. For H2, we conducted four linear regression analyses with Stroop reaction time, Stroop accuracy, Simon reaction time, and Simon accuracy as dependent variables, and age, time spent on social media (30 min–5 hours), and PSMU severity (BSMAS total score) as predictors. For H3, we ran hierarchical regressions where time on social media and the sum of BSMAS items 1, 3, and 6 were entered in Step 1, and the sum of items 2, 4, and 5 ("loss of control") was entered in Step 2, for each of the four cognitive measures. For H4, we ran four regression models including sex (0 = male, 1 = female), centered total PSMU severity (BSMAS total score), and their interaction term (sex × BSMAS) as predictors.

Ethics

Participants completed the study through *Prolific*, with data collected via a secure online platform. All subjects were informed about the study procedures and all provided informed consent before commencing with the study. The study were carried out in accordance with the Declaration of Helsinki and was approved by the institutional ethics review board in the Faculty of Health Sciences at the Camilo José Cela University. Data collection was completed efficiently within a two-weeks' timeframe, and participant feedback was consistently monitored to address any unforeseen issues promptly.

RESULTS

See Table 2 for descriptive data of the sample.

Table 3 shows Spearman correlation analyses between the study variables.

BSMAS scores correlated positively with daily social media time of use ($r = .67$, $p < .05$) and with Stroop reaction times ($r = .65$, $p < .05$) but did not correlate significantly with Simon reaction times ($r = .05$, $p > .05$). Regression analyses including daily social media time are reported below. Regarding accuracy measures, BSMAS scores did not correlate with Stroop accuracy ($r = -.06$, $p = .05$) or Simon accuracy ($r = -.04$, $p = .08$). Age was not significantly correlated with any cognitive outcomes. Stroop and Simon reaction times were moderately correlated ($r = .58$, $p < .001$). To examine the contributions of PSMU beyond age and daily social media time, multiple regression analyses were conducted (Table 4).

For Stroop reaction time, the overall model was significant. Daily social media time was significantly associated with Stroop reaction time ($\beta = .28$, $p < .001$). Age was not associated with Stroop reaction time. ($p = .37$). PSMU severity (BSMAS total) was not significantly associated with Stroop reaction time once daily use and age were included ($p = .29$). For Stroop accuracy, none of the predictors were

Table 2. Descriptive statistics for the main variables

		BSMAS		Stroop Time		Simon Time	
		Mean	SD	Mean	SD	Mean	SD
Sex	Males	15.06	4.73	1.60	.46	1.62	.49
	Females	16.84	4.45	1.66	.47	1.73	.46
Educational Level	Secondary Education	15.70	5.15	1.62	.34	1.73	.52
	Baccalaureate	15.98	4.28	1.60	.42	1.66	.51
	Bachelor's Degree	15.82	4.71	1.64	.48	1.67	.48
	PhD	16.98	4.67	1.56	.47	1.68	.41
Daily Social Media Time	0–30 min	10.03	3.05	1,47	.26	1.54	.33
	30–60 min	13.00	3.99	1.58	.40	1.62	.40
	1–3 h	15.59	4.17	1.60	.40	1.67	.47
	3–5 h	17.41	4.42	1.66	.49	1.69	.48
	>5 h	18.66	4.75	1.79	.67	1.73	.59

Note: BSMAS = Bergen Social Media Addiction Scale.

Table 3. Spearman correlation coefficients between age, PSMU, attention accuracy and response times and inhibitory control times

Variable	BSMAS	Age	Stroop accuracy	Simon accuracy	Stroop RT	Simon RT	Daily social media time of use
BSMAS	1.00	.	.	.	.	.	.
Age	.02	1.00	.	.	.	.	.
Stroop accuracy	−.06*	−.01	1.00	.	.	.	.
Simon accuracy	−.04	.01	.18*	1.00	.	.	.
Stroop RT	.65*	.04	−.22*	−.12*	1.00	.	.
Simon RT	.049	.03	−.15*	−.02	.58**	1.00	.
Daily social media time of use	.67*	.04	−.01	.03	.02	−.05	1.00

Note: Stroop RT and Simon RT = reaction times on Stroop and Simon tasks. * p < .05. **p < .001. BSMAS = Bergen Social Media Addiction Scale. Social media time of use was coded as 0–30 min, 30 min–1 hour, 1–3 h, 3–5 h, or more than 5 h (See section Measures).

Table 4. Multiple regression models examining cognitive performance from age, daily social media time, and PSMU

Variable	Predictor	B	SE B	β	t	*p*
Stroop RT	Age	0.00	0.003	.05	0.90	.37
	Daily social media time	0.04	0.01	.28	3.90	< .001
	BSMAS total	0.01	0.01	.07	1.06	.29
Model fit: R^2 = .056, Adjusted R^2 = .053, F (3, 939) = 18.54, p < .001						
Stroop Accuracy	Age	−0.05	0.06	−.06	−0.80	.42
	Daily social media time	−0.06	0.07	−.07	−0.90	.37
	BSMAS total	−0.03	0.02	−.10	−1.40	.16
Model fit: R^2 = .011, Adjusted R^2 = .008, F(3, 939) = 3.47, p = .062						
Simon Reaction Time	Age	0.01	0.004	.08	1.30	.19
	Daily social media time	0.01	0.01	.06	1.00	.32
	BSMAS total	0.00	0.01	.04	0.65	.52
Model fit: R^2 = .009, Adjusted R^2 = .006, F(3, 939) = 2.91, p = .089						
Simon Accuracy	Age	−0.03	0.05	−.05	−0.60	.55
	Daily social media time	−0.05	0.06	−.06	−0.90	.38
	BSMAS total	−0.02	0.02	−.08	−1.40	.15
Model fit: R^2 = .007, Adjusted R^2 = .004, F (3, 939) = 2.28, p = .128						

Note: Stroop RT and Simon RT = reaction times on Stroop and Simon tasks. BSMAS = Bergen Social Media Addiction Scale.

significant (p > .37). For Simon reaction time, the overall model was not significant. Age, daily social media time, and PSMU were not significantly associated with Simon reaction time (p > .19). For Simon accuracy, none of the predictors were significant (p > .38) (Table 5).

In the hierarchical regression analyses, for each cognitive outcome, Step 1 included daily social media time and the non–loss-of-control BSMAS items (items 1, 3, 6), which was significantly associated with Stroop reaction times (both p < .001). In Step 2, the loss-of-control dimension was added, but this did not produce a significant change in the model (β = .08, p = .27). For Stroop accuracy, Simon reaction time, and Simon accuracy, no predictors reached significance in either Step 1 or Step 2 (p > .11), and the loss-of-control dimension was not significant in any of these models (Table 6).

A significant Sex × BSMAS interaction emerged for Stroop reaction time (β = .14, p = .018). Follow-up estimates showed that the positive association between PSMU and slower Stroop performance was stronger among females than males, indicating that higher PSMU levels were more closely linked to reduced selective attention efficiency in women.

No significant sex interactions were found for Stroop accuracy, Simon reaction time, or Simon accuracy (p > .11).

DISCUSSION

This study examined whether PSMU is associated with deficits in selective attention and inhibitory control in young adults. Drawing on previous findings that propose executive difficulties as consequences of maladaptive social media engagement (Liu et al., 2024; Zhang et al., 2023), we investigated whether PSMU was associated with performance on the Stroop task, assessing selective attention (Macleod, 1992; Scarpina & Tagini, 2017), and the Simon task, assessing inhibitory control (Borgmann, Risko, Stolz, & Besner, 2007; Simon, 1967).

H1 proposed that higher PSMU would relate to poorer selective attention and inhibitory control. This hypothesis was partially supported: PSMU was associated with slower Stroop reaction times, indicating increased attentional interference, which aligns with prior work suggesting that PSMU is associated with difficulties in filtering task-relevant information in the presence of competing stimuli

Table 5. Hierarchical Regression Testing Unique Effects of Loss-of-Control sub-items

Step	Predictor	B	SE B	β	t	*p*
Model Fit		R^2 = .061, Adj R^2 = .058, F(2, 940) = 30.52, p < .001				
Step 1	Social media time of use	0.04	0.01	.28	3.80	< .001
	BSMAS score (1,3,6)	0.04	0.01	.32	4.50	< .001
Model Fit		R^2 = .063, Adj R^2 = .059, ΔR^2 = .002, F-change(1.939) = 2.11, p = .27				
Step 2	Loss of control (2,4,5)	0.01	0.01	.08	1.10	.27

Note: BSMAS = Bergen Social Media Addiction Scale. Social media time of use was coded as 0–30 min, 30 min–1 hour, 1–3 h, 3–5 h, or more than 5 h (See section Measures).

Table 6. Moderation models testing sex x PSMU interaction

	Predictor	B	SE B	β	t	*p*
Stroop RT	Age	0.00	0.003	.05	0.90	.37
	Daily social media time	0.04	0.01	.28	3.90	< .001
	BSMAS total	0.01	0.01	.08	1.25	.21
	Sex × BSMAS	0.02	0.01	.14	2.38	.018
	Model fit: R^2 = .073, Adjusted R^2 = .069, F(4, 938) = 18.43, p < .001					
Stroop accuracy	Age	−0.05	0.06	−.06	−0.80	.42
	Daily social media time	−0.06	0.07	−.07	−0.90	.37
	BSMAS total	−0.03	0.02	−.10	−1.40	.16
	Sex × BSMAS	−0.01	0.02	−.04	−1.15	.23
	Model fit: R^2 = .013, Adjusted R^2 = .009, F(4, 938) = 3.08, p = .078					
Simon RT	Age	0.01	0.004	.08	1.30	.19
	Daily social media time	0.01	0.01	.06	1.00	.32
	BSMAS total	0.01	0.01	.08	1.10	.27
	Sex × BSMAS	0.01	0.01	.05	1.02	.31
	Model fit: R^2 = .012, Adjusted R^2 = .008, F(4, 938) = 2.82, p = .092					
Simon accuracy	Age	−0.03	0.05	−.05	−0.60	.55
	Daily social media time	−0.05	0.06	−.06	−0.90	.38
	BSMAS total					
	Sex x BSMAS	−0,01	0.02	−.03	−0.75	.45
	Model fit: R^2 = 0.009, Adjusted R^2 = 0.005, F(4, 938) = 2.15, p = .073					

Note: BSMAS = Bergen Social Media Addiction Scale. Social media time of use was coded as 0–30 min, 30 min–1 hour, 1–3 h, 3–5 h, or more than 5 h (See section Measures).

(Cain et al., 2016; Farchakh et al., 2022; Wegmann et al., 2020). However, no significant associations emerged for the Simon task. Given that the Stroop task draws on semantic conflict resolution and higher-order attentional processes (Macleod, 1992), whereas the Simon task taps basic spatial response inhibition (Borgmann et al., 2007), our findings suggest that PSMU affects domain-specific components of cognition, impairing selective attention more than fundamental inhibitory mechanisms. This extends emerging claims that attentional control may be particularly vulnerable to overstimulation from algorithmic social media environments (Reed, 2023; Zhang et al., 2023).

H2 predicted that associations would remain significant after accounting for age and daily social media time. This hypothesis was only partially supported. Although PSMU correlated with Stroop reaction times, regression analyses showed that daily social media time, rather than PSMU symptoms, were uniquely associated with slowed performance. The substantial correlation between PSMU severity and daily social media use suggests a considerable overlap between these constructs. This raises the question of whether the BSMAS total score may capture aspects beyond intensive use. However, the present findings suggest that usage duration may play a more prominent role in explaining cognitive performance, highlighting the importance of distinguishing between exposure and problematic engagement. These results imply that attentional inefficiencies may arise from exposure duration rather than addictive symptom severity (Andreassen et al., 2016). Thus, cognitive consequences may depend on the quantity of use as much as its problematic qualities, emphasizing the importance of distinguishing time spent online from maladaptive engagement.

H3 posited that the *loss-of-control* component of PSMU (items 2, 4, 5) would uniquely be associated with cognitive performance. This hypothesis was not supported, as adding the loss-of-control component did not account for additional explained Stroop variance (ΔR^2 = .002, p = .27) once other BSMAS components were included. While theoretical models highlight loss of control as a defining addiction feature (Griffiths, 2022), our results indicate that cognitive correlates reflect broader symptom constellations rather than this facet alone. Future studies incorporating tasks that capture sustained impulsivity or delay sensitivity (Li, Zhang, & Hu, 2025; Wright, Lipszyc, Dupuis, Thayapararajah, & Schachar, 2014) may reveal stronger associations with loss-of-control.

H4 proposed that sex would moderate associations between PSMU and cognitive performance. This hypothesis was supported only for selective attention. The Sex × PSMU interaction indicated that the relationship between PSMU and Stroop performance was stronger among women. This aligns with prior evidence that women display higher PSMU symptoms (Varchetta et al., 2024; Keyte et al., 2021). This is also consistent with meta-analytic findings showing gender differences in problematic online behaviors, with women showing higher tendencies toward social media use and men toward gaming-related behaviors (Su, Han, Yu, Wu, & Potenza, 2020). Women also tend to engage in more emotionally driven social media behaviors (Muscanell & Guadagno, 2012; Tifferet, 2020), which may increase cognitive load and attentional vulnerability. No moderation emerged for Simon performance, suggesting that sex effects are restricted to attentional demands rather than inhibitory processes.

Overall, the present study shows that PSMU is associated with reduced selective attention particularly via slowed reaction times and that women appear to be more vulnerable than men, while leaving basic inhibitory control largely intact. These findings contribute to ongoing theoretical debates by suggesting that the cognitive consequences of PSMU are selective rather than global, and by highlighting the need to differentiate problematic symptoms from duration of use when assessing their impact on cognitive functioning.

From a clinical and public health perspective, these findings suggest that interventions should not only target problematic symptoms, but also overall exposure to social media. Experimental evidence indicates that reducing smartphone and social media use may improve attentional performance, suggesting that some cognitive effects could be modifiable (Hall, Kleszczewski, & Turner, 2021; He, Turel, & Bechara, 2020). In clinical contexts, this highlights the potential value of digital self-regulation strategies, such as monitoring use, managing notifications, and limiting daily exposure. At a broader level, these results support the need for public health initiatives promoting healthier digital habits, including digital literacy and awareness programs. The stronger associations observed among women further suggest that gender-sensitive approaches may be warranted in both prevention and intervention efforts (Su et al., 2020; Varchetta et al., 2024).

Taken together, the present findings contribute to ongoing debates regarding the cognitive correlates of problematic social media use by suggesting that associations with cognitive performance may be more closely related to usage duration than to symptom severity. This highlights the importance of distinguishing between intensive and problematic use, and calls for greater conceptual clarity in the assessment of PSMU. From a theoretical perspective, the results are consistent with dual-process and executive-control frameworks, which propose that repeated engagement with salient and rewarding cues may strengthen automatic attentional capture while increasing demands on top-down control processes (Brand et al., 2019; Montag et al., 2021; Wegmann et al., 2020). In the context of PSMU, this may help explain why higher problematic engagement was associated with slower Stroop performance, a task requiring selective attention and conflict resolution, whereas no comparable association emerged for Simon task performance. Thus, the present findings suggest that the cognitive correlates of PSMU may be domain-specific rather than reflecting a generalized impairment in executive functioning. More broadly, these findings contribute to current discussions on whether existing self-report measures adequately capture the complexity of problematic use, particularly when substantial overlap with usage time is observed.

STRENGTHS AND LIMITATIONS

This study contributes to the growing body of research examining the relationship between PSMU and cognitive performance by combining a validated self-report measure (BSMAS) with objective cognitive tasks, which may help to reduce susceptibility to common method variance (Podsakoff, MacKenzie, & Podsakoff, 2012). It also employed a large sample ($N = 943$) and was guided by an a priori power analysis. However, causality cannot be inferred, as the design was correlational. It is important to note that the BSMAS is a self-report instrument and does not rely on clinical diagnostic criteria, which may limit its ability to fully distinguish between intensive social media use and PSMU. This limitation is particularly relevant in light of ongoing discussions on the classification of behavioral addictions in frameworks such as the DSM-5 and ICD-11. Moreover, each cognitive task was brief (e.g., 20 Stroop trials), which, despite acceptable reliability estimates, lies at the lower end of standard task length. Future research should thus employ longer test bouts. Additionally, unmeasured confounders, such as sleep, may have influenced results, given its associations with both PSMU (Chen et al., 2023) and cognition (Killgore & Weber, 2013). Studies examining whether sleep mediates the relationship between PSMU, social media time, and cognitive impairments are therefore warranted. Future research may also benefit from incorporating clinically informed assessments to further clarify the distinction between problematic and intensive use.

CONCLUSION

This study aimed to shed light on the cognitive correlates of problematic social media use. PSMU was associated with poorer selective attention and attentional interference, but not with basic spatial response inhibition. These findings highlight impairments of attentional control as a potential mechanism linking PSMU to real-world difficulties in terms of concentration and goal-directed behavior. The results also emphasize the close intertwining of PSMU with daily usage time and the moderating role of sex, both of which should be corroborated by future studies.

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APPENDIX

Computerized version of the Stroop test

Instructions

The function 'mostrar_instrucciones_Stroop' presents the participant with:

- A description of the test.
- Instructions on how to respond.
- An explanation of the conditions being evaluated.

The participant can start the test by clicking the "Start Stroop Test" button.

Stimulus generation

The function 'mostrar_stroop_test' randomly generates a series of 20 stimuli:

- Each stimulus consists of a word (e.g., "Red") and a text color (e.g., blue).
- The stimulus can be congruent (the color and word meaning match) or incongruent (they do not match).
- 50% of the stimuli are congruent, and 50% are incongruent to ensure balance in the test.

These stimuli are stored in the variable 'st.session_state.stroop_test_items', ensuring data persistence throughout the session.

Stimulus Presentation

Each stimulus is displayed one at a time on the screen:

- The word appears centered and styled in the corresponding color.
- The participant must press either the "Correct" or "Incorrect" button to register their response.

Reaction time is measured from when the stimulus appears until a button is pressed.

Response recording

The function 'procesar_respuesta_stroop' evaluates each response:

- It determines whether the response is correct or incorrect by comparing it to the stimulus congruency.
- It records the participant's reaction time.
- It saves the results in a list for further analysis.

Test completion

Once the participant completes all 20 stimuli:

- The results are stored in a structured format for later analysis.
- The test concludes with a thank-you message.

Computerized version of the Simon task

In this test, a colored circle (red or green) appears on the screen, either on the left or right. The participant must ignore the circle's position and respond based on its color:

- Red circle → Press the "right" button.
- Green circle → Press the "left" button.

The test includes two conditions:

1. Congruent condition: The circle's position matches the side associated with its color (e.g., a green circle on the left).
2. Incongruent condition:" The circle's position does not match the side associated with its color (e.g., a green circle on the right).

The test measures:

- "Reaction time:" The time it takes for the participant to respond.
- "Accuracy:" The proportion of correct responses.

"Technical Implementation"
Python and the Streamlit library were used to create an interactive interface that presents the stimuli, records responses, and calculates reaction times.

Test instructions

The function 'mostrar_instrucciones_simon' presents the participant with:

- A description of the test.
- Instructions on how to respond.
- An explanation of the conditions being evaluated.

The participant can start the test by clicking the "Start Simon Effect Test" button.

Stimulus generation

The function 'mostrar_simon_test' dynamically generates the stimuli:

- Each stimulus consists of a color (red or green) and a position (left or right).
- Stimuli are generated randomly while ensuring a balanced number of congruent and incongruent trials.

The stimuli are stored in 'st.session_state.simon_current_trial' to ensure session persistence.

Stimulus presentation

Each stimulus appears on the screen:

- The circle is displayed in its corresponding color (red or green) and its assigned position (left or right).
- The interface uses 'st.markdown' to present the stimuli with a clear, centered design.

Response recording

The participant selects their response using one of two buttons:

- "Left" for a green circle.
- "Right" for a red circle.

The function records:

- Reaction time: Measured from stimulus presentation to button selection.
- Congruency: Whether the position and color match the defined rules.

Results storage

Each response is stored in 'st.session_state.simon_responses' as a dictionary containing:

- Stimulus color.
- Circle position.
- Participant's response.
- Reaction time.
- Congruency indicator.

Test completion

After completing 20 trials:

- The test displays a success message and records the results.
- The data is ready for export or further analysis.