Journal of Urban Development in Education
Vol. 2, No. 1, 2026, pp. 24-32



Contents lists available at Journal Nalatama

Journal of Urban Development in Education

Journal homepage: https://journal.nalatama.org/index.php/jude

Present in Class, Elsewhere Online: Fear of Missing Out as a Modest Predictor of Cyberslacking among Indonesian First Year Health Sciences Students

Ahmad Fa'iz Nuzula Husnayain[1], Farrel Algaze[2]
[1]Universitas Jambi, Indonesia
[1]Universitas Dinamika Bangsa Jambi, Indonesia

Article Info

Article history:

Received Sep 7th, 2026
Accepted Oct 20th, 2026

Keyword:

Basic psychological needs; Cyberloafing; Digital distraction; Effect size; Sensitivity analysis

ABSTRACT

Cyberslacking, the nonacademic use of the internet during instruction, may undermine learning in demanding health sciences curricula. Drawing on Self Determination Theory, this study examined whether fear of missing out (FoMO) predicted cyberslacking among first year students and how robust this prediction was to unmeasured confounding. In a predictive correlational design, 79 first year students of the Faculty of Medicine and Health Sciences, Universitas Jambi, Indonesia, completed the Online Fear of Missing Out Inventory (α = .86) and the Cyberslacking Scale (α = .91). Simple linear regression was supplemented by sensitivity analyses for omitted variable bias. FoMO positively predicted cyberslacking (β = .27, 95% CI [.05, .46], p = .016), yet it explained only 7.3% of the variance, a small effect (f^2 = .08). The inference would be overturned if 19% of the estimate reflected bias or if an omitted confounder, such as device exposure, correlated about .25 with both variables. FoMO was therefore a statistically significant but modest and only moderately robust predictor, with more than 90% of the variance in cyberslacking attributable to other factors. FoMO oriented digital literacy should be one component of broader strategies addressing self regulation, instructional engagement, and classroom device norms.

© 2025 The Authors. Published by Nalatama.
This is an open access article under the CC BY license
(Creative Commons Attribution 4.0 International License)

Corresponding Author:

Ahmad Fa'iz Nuzula Husnayain,
Universitas Jambi, Indonesia
Email: nuzulahusnayain@gmail.com

Introduction

The digitalization of higher education has turned the internet into an indispensable learning resource, but it has also made the lecture hall one of the most contested spaces for students' attention. In Indonesia, internet penetration reached 79.5% of the population in 2024, with Generation Z forming the largest share of users (Asosiasi Penyelenggara Jasa Internet Indonesia [APJII], 2024), so that almost every undergraduate now attends lectures with a connected device within reach. One consequence of this ubiquitous connectivity is cyberslacking, also termed cyberloafing, which refers to the use of the internet for nonacademic purposes

while instruction is in progress (Akbulut et al., 2016; Taneja et al., 2015). Akbulut et al. (2016) distinguished five forms of this behavior, namely sharing, shopping, real time updating, accessing online content, and gaming or gambling. The concern is not merely disciplinary. In class multitasking with social media and text messaging has been associated with lower grade point averages (Junco, 2012), nonacademic internet use during lectures has predicted poorer examination performance even after students' intellectual ability was taken into account (Ravizza et al., 2017), and student cyberloafing has been linked with weaker academic performance (Wu et al., 2018).

These risks are amplified in health sciences education. Programs such as medicine, nursing, pharmacy, public health, and psychology combine dense theoretical content with the expectation that students develop the sustained attention and analytical reasoning required for later professional practice. A recent grounded theory study showed that academic cyberslacking among medical students is triggered by low perceived autonomy, phone use as a way of coping with stress and fatigue, peer modeling, lectures perceived as unengaging, and incoming notifications, and that it is sustained by recommendation algorithms and depleted self control (Zhou et al., 2025). The first year of study adds a further layer of vulnerability. First year students must adapt to a new academic culture while rebuilding their social networks, a transition in which belonging needs are likely to be salient and in which online platforms become a primary channel for maintaining social connection.

Self Determination Theory (SDT) provides a coherent framework for explaining why these conditions may translate into cyberslacking. SDT posits that optimal functioning depends on the satisfaction of three basic psychological needs, namely autonomy, competence, and relatedness, and that the thwarting of these needs gives rise to compensatory motives and behaviors that are often maladaptive (Deci & Ryan, 2000). Within this framework, Przybylski et al. (2013) conceptualized fear of missing out (FoMO) as a pervasive apprehension that others may be enjoying rewarding experiences in one's absence, accompanied by a desire to remain continuously connected with what others are doing. Their studies showed that FoMO is rooted in deficits in basic need satisfaction and that individuals high in FoMO are more likely to engage with social media during university lectures (Przybylski et al., 2013). The compensatory internet use perspective similarly holds that online activity often serves to regulate unmet psychological needs or negative affect rather than being an end in itself (Kardefelt-Winther, 2014), and process models of problematic technology use treat FoMO as an affective and cognitive vulnerability that motivates repeated checking of social information (Elhai et al., 2021). Taken together, these perspectives imply an a priori sequence: when relatedness needs are insufficiently satisfied in an intensive academic environment, FoMO intensifies, and the resulting urge to monitor peers' activities competes with the lecture for attention, which manifests behaviorally as cyberslacking, particularly in its sharing and real time updating forms.

Empirical evidence broadly supports this reasoning but also reveals considerable heterogeneity. A comprehensive meta analysis of 86 effect sizes from 55,134 participants found that associations between FoMO and various forms of internet use ranged from $r = .11$ to $r = .63$ (Akbari et al., 2021), and a second meta analysis reported robust positive associations between FoMO and both the use and the problematic use of social networking sites (Fioravanti et al., 2021; see also Tandon et al., 2021). Evidence from educational settings is consistent in direction. FoMO has been associated with social media engagement during lectures (Alt, 2015, 2017), with more frequent disruption of daily activities by smartphone notifications and a surface approach to learning (Rozgonjuk et al., 2019), and with a range of maladaptive behaviors among college students (McKee et al., 2022). In Indonesia, Alvaridzi and Ardelia (2025) reported a positive correlation between FoMO and cyberslacking among university students. The evidence is nevertheless not uniform. Ningrum and Pratisti (2026) found no direct positive relationship between FoMO and cyberslacking, with the association operating instead through self regulation, whereas deficient self control has shown a considerably stronger association with cyberslacking ($r = .52$; Li & Liu, 2022), and self regulation has repeatedly been implicated in student cyberloafing (Gökçearslan et al., 2016; Zamzani et al., 2024). A meta analysis of cyberloafing in organizational settings likewise indicates that the behavior has multiple personal and situational antecedents (Mercado et al., 2017).

Two features of this literature limit the conclusions that can be drawn from it. First, most studies, including those conducted in Indonesia, have reported bivariate associations without asking how vulnerable these associations are to variables that were not measured. This question matters because heavier device use is associated with problematic smartphone use and cyberloafing (Gökçearslan et al., 2016) and plausibly with FoMO as well, so that a bivariate association may partly reflect exposure rather than the motivational process

described by SDT. Second, statistical significance has often been reported without an explicit judgment of practical magnitude, although effect sizes in individual differences research require calibrated interpretation (Funder & Ozer, 2019; Gignac & Szodorai, 2016). The present study addresses both issues. Rather than merely replicating a bivariate model in a new setting, it (a) derives the link between FoMO and cyberslacking deductively from SDT and the compensatory internet use perspective, (b) quantifies how strong an omitted confounder, such as device exposure or study program, would have to be to overturn the inference, using sensitivity analyses for omitted variable bias (Frank, 2000; Frank et al., 2013) that are rarely applied in this literature, and (c) calibrates the magnitude of the effect against meta analytic evidence and contemporary effect size benchmarks. These questions are examined among first year students in a faculty of medicine and health sciences located outside Indonesia's main metropolitan centers, a population that combines a demanding curriculum with the social pressures of the transition to university and that remains underrepresented in this literature.

Accordingly, this study aimed to examine FoMO as a predictor of cyberslacking among first year students of the Faculty of Medicine and Health Sciences (FKIK), Universitas Jambi. One hypothesis and one robustness question guided the study. Hypothesis 1 (H1) stated that FoMO positively predicts cyberslacking. The robustness question asked how strong an unmeasured confounder would need to be to invalidate this prediction. In view of the heterogeneity of previous estimates and the multicausal nature of cyberslacking, the effect was expected to be positive but small to moderate, implying that FoMO would account for only part of the variance in cyberslacking.

Method

This study employed a quantitative predictive correlational design, which examines not only whether variables are related but also the extent to which one variable statistically predicts another (Periantalo, 2019). Data were collected at a single time point through an online questionnaire administered with Google Forms. The target population was first year students (2025 cohort) of FKIK Universitas Jambi. Participants were recruited through purposive sampling using four inclusion criteria: (a) being registered as a first year FKIK student attending courses in the current semester, (b) owning and actively using at least one social media platform, (c) using a digital device (a smartphone, a laptop, or both) during lectures, and (d) being willing to participate voluntarily. Consent was indicated by agreeing to complete the questionnaire. The final sample consisted of 79 students from five study programs (Table 1). Psychology students formed the largest group (41.8%), and the mean self reported daily device use was 6.11 hours, ranging across programs from 5.50 hours among Nursing students to 7.46 hours among Medicine students.

Table 1. Participant characteristics by study program

Study program	*n*	%	Mean daily device use (hours)
Medicine	13	16.5	7.46
Psychology	33	41.8	5.85
Nursing	12	15.2	5.50
Public Health	11	13.9	6.27
Pharmacy	10	12.7	5.80
Total	**79**	**100.0**	**6.11**

Note. Daily device use was self reported as the average number of hours of device use per day. The total mean is weighted by group size.

FoMO was measured with the Online Fear of Missing Out Inventory developed by Sette et al. (2020) and adapted into Indonesian by Kurniawan and Utami (2022). The instrument contains 20 items covering four dimensions, namely anxiety, need to belong, addiction, and need for popularity, rated on a five point Likert scale from 1 (very untrue of me) to 5 (very true of me), so that total scores range from 20 to 100. Cyberslacking was measured with the Cyberslacking Scale developed by Akbulut et al. (2016) and adapted for Indonesian university students by Simanjuntak et al. (2019). The scale contains 24 items covering five dimensions, namely sharing, shopping, real time updating, accessing online content, and gaming or gambling, rated on a five point frequency scale from 1 (never) to 5 (always), so that total scores range from 24 to 120. Higher scores on both instruments indicate higher levels of the construct. In the present sample, internal consistency was good for the FoMO inventory (Cronbach's α = .856, 95% CI [.805, .907]) and excellent for the Cyberslacking Scale (α =

.909, 95% CI [.880, .938]), both well above the conventional threshold of .70 (Nunnally & Bernstein, 1994). Study program and average daily device use (in hours) were recorded to describe the exposure context of the sample and were not part of the a priori predictive model.

Data were analyzed with JASP in four stages. First, descriptive statistics were computed, mean scores were compared with the theoretical midpoint of each scale using one sample *t* tests, and levels were categorized on the basis of the hypothetical mean and standard deviation of each instrument (Periantalo, 2019). Second, the distribution of each variable was examined with the Shapiro–Wilk test as a prerequisite for parametric analysis (Tabachnick & Fidell, 2019). Because the normality assumption of linear regression strictly concerns the residuals rather than the observed variables (Williams et al., 2013), these results were treated as supportive rather than conclusive evidence that the assumption was satisfied. Third, H1 was tested with simple linear regression, reporting the unstandardized coefficient (*B*) with its 95% confidence interval, the standardized coefficient (β), R^2, and Cohen's f^2. Magnitudes were interpreted against Cohen's (1988) conventions (f^2 = .02, .15, and .35 for small, medium, and large effects) and against empirically derived benchmarks for individual differences research (*r* = .10, .20, and .30 for relatively small, typical, and relatively large effects; Gignac & Szodorai, 2016), and the correlation was additionally corrected for the unreliability of both measures (Nunnally & Bernstein, 1994). Fourth, because the model contained no covariates, the robustness of the FoMO coefficient to omitted variables was evaluated with two complementary indices computed from the regression estimates. The impact threshold for a confounding variable (ITCV) expresses the minimum product of an omitted variable's correlations with the predictor and the outcome that would render the coefficient nonsignificant (Frank, 2000). The percent bias required to invalidate the inference, together with the robustness of inference to replacement (RIR), expresses the proportion of the estimate, and the corresponding number of cases, that would have to be attributable to bias for the inference to change (Frank et al., 2013). All tests were two tailed with α = .05. A sensitivity power analysis based on the noncentral *F* distribution (Cohen, 1988; Faul et al., 2009) indicated that, with *N* = 79, α = .05, and power of .80, the design could reliably detect effects of $f^2 \geq .10$ ($R^2 \approx .09$) for a single predictor. Because the design was cross sectional and relied on self report measures, all analyses were interpreted as tests of prediction rather than causation.

Results and Discussions

Table 2 summarizes the descriptive statistics, reliability coefficients, and normality tests. The mean FoMO score was 52.56 (*SD* = 11.26), equivalent to a mean item score of 2.63 on the five point scale. This value fell within the moderate category but was significantly below the theoretical midpoint of 60, $t(78) = -5.87$, $p < .001$, $d = -0.66$. The mean cyberslacking score was 78.52 (*SD* = 15.42), equivalent to a mean item score of 3.27, which also fell within the moderate category but was significantly above the theoretical midpoint of 72, $t(78) = 3.76$, $p < .001$, $d = 0.42$. This asymmetry is informative in its own right: participants reported engaging in nonacademic online activity during lectures more often than the scale midpoint while reporting FoMO below the midpoint, which offers a first descriptive indication that cyberslacking in this population cannot be reduced to FoMO alone. Shapiro–Wilk tests indicated no departure from normality for either FoMO ($W = .987$, $p = .617$) or cyberslacking ($W = .984$, $p = .411$).

Table 2. Descriptive statistics, reliability, and normality of the study variables

Variable	*M*	*SD*	Min–Max	Item *M*	α	95% CI for α	*W*	*p*
FoMO	52.56	11.26	26–86	2.63	.856	[.805, .907]	.987	.617
Cyberslacking	78.52	15.42	34–110	3.27	.909	[.880, .938]	.984	.411

Note. *N* = 79. Item *M* = scale mean divided by the number of items. Possible score ranges were 20 to 100 for FoMO and 24 to 120 for cyberslacking, with theoretical midpoints of 60 and 72, respectively. Moderate category boundaries (hypothetical mean ± 1 *SD*) were 46.67 to 73.33 for FoMO and 56.00 to 88.00 for cyberslacking. *W* = Shapiro–Wilk statistic.

Table 3 presents the simple linear regression used to test H1. The model was statistically significant, $F(1, 77) = 6.07$, $p = .016$. FoMO positively predicted cyberslacking, $B = 0.370$, $SE = 0.150$, 95% CI [0.071, 0.669], β = .27, $t(77) = 2.46$, $p = .016$, yielding the regression equation Cyberslacking = 59.06 + 0.370 (FoMO). A difference of one standard deviation in FoMO (11.26 points) therefore corresponded to a difference of approximately 4.2 points on the 96 point range of possible cyberslacking scores. H1 was supported. The magnitude of this prediction, however, was modest. FoMO explained 7.3% of the variance in cyberslacking ($R^2 = .073$; adjusted $R^2 = .061$), corresponding to $f^2 = .08$, which lies between Cohen's (1988) small and medium benchmarks and closer to the former. The 95% confidence interval of the correlation, $r = .27$ [.05, .46], was wide, and its lower

bound approached zero. Correcting the correlation for the unreliability of both measures raised it only to approximately .31, or 9.4% of shared variance, which indicates that the modest effect is not an artifact of measurement error. Moreover, the observed effect lies slightly below the smallest effect that the design could detect with a power of .80 (f^2 = .10), so the point estimate should be regarded as imprecise.

Table 3. Simple linear regression of cyberslacking on FoMO (H1)

Predictor	*B*	*SE*	95% CI for *B*	β	*t*	*p*
Constant	59.06	8.077	[42.98, 75.14]		7.313	< .001
FoMO	0.370	0.150	[0.071, 0.669]	.270	2.463	.016

Note. R = .270, R^2 = .073, adjusted R^2 = .061, $F(1, 77)$ = 6.07, p = .016, f^2 = .08. B = unstandardized coefficient; β = standardized coefficient.

Because the regression contained no covariates, the robustness of this inference to omitted variables was quantified (Table 4). The FoMO coefficient would remain statistically significant as long as it exceeded 0.299, which means that 19.3% of the observed estimate would have to be attributable to bias to invalidate the inference; equivalently, about 15 of the 79 cases would have to be replaced by cases in which FoMO and cyberslacking were unrelated (Frank et al., 2013). In terms of omitted variables, a confounder would need an impact of about .06, that is, correlations of approximately .25 with both FoMO and cyberslacking, to render the coefficient nonsignificant (Frank, 2000). To illustrate, a confounder correlated at .20 with both variables would leave the coefficient significant (partial r = .24, p = .035), whereas a confounder correlated at .30 with both would not (partial r = .20, p = .083). The inference is therefore robust to weak confounding but not to confounding of moderate strength.

Table 4. Sensitivity of the FoMO coefficient to omitted variable bias

Index	Value	Interpretation
Threshold for significance (*B*)	0.299	Smallest coefficient that remains significant at α = .05 with N = 79
Percent bias to invalidate the inference	19.3%	Share of the estimate that would have to be due to bias
Robustness of inference to replacement	15 cases	Cases that would have to be replaced by cases with no effect
Impact threshold for a confounding variable	.06	Minimum product of a confounder's correlations with FoMO and cyberslacking
Component correlation of the confounder	.25	Required correlation with each variable when both correlations are equal

Note. Indices were computed from B = 0.370, SE = 0.150, and N = 79 following Frank (2000) and Frank et al. (2013).

The central finding of this study is best characterized as a statistically significant but practically modest association. FoMO predicted cyberslacking in the hypothesized direction, yet it accounted for less than one tenth of the variance, leaving more than 90% of the individual differences in cyberslacking unexplained. This magnitude frames every interpretation that follows. Against the meta analytic range of associations between FoMO and internet use (r = .11 to .63; Akbari et al., 2021), the present estimate (r = .27) lies in the lower part of the distribution, and it is about half the size of the association between deficient self control and cyberslacking reported among Chinese college students (r = .52; Li & Liu, 2022). At the same time, an effect of this size is not negligible in individual differences research, in which r = .20 represents a typical effect and r = .30 a relatively large one (Gignac & Szodorai, 2016), and small effects on a behavior that recurs in every lecture may accumulate across a semester (Funder & Ozer, 2019). The appropriate conclusion is therefore neither that FoMO is a principal driver of cyberslacking nor that it is irrelevant, but that FoMO is one modest contributor within a multicausal process.

The direction of the effect replicates earlier findings. It is consistent with the positive correlation reported among Indonesian university students by Alvaridzi and Ardelia (2025), with the association between FoMO and social media engagement during lectures documented by Alt (2015), and with evidence that FoMO is associated with more frequent disruption of ongoing activities by smartphone notifications and with surface learning (Rozgonjuk et al., 2019). The modest magnitude, however, is equally consistent with research in which the direct contribution of FoMO weakened or disappeared once regulatory processes were modeled (Ningrum

& Pratisti, 2026). Read together, these findings suggest that FoMO generates a motivational pull toward online social information, but whether that pull is converted into cyberslacking depends substantially on self regulation, the instructional context, and the device habits that students bring to the classroom (Gökçearslan et al., 2016; Mercado et al., 2017; Zhou et al., 2025).

From the perspective of SDT, which guided the hypothesis a priori, both the presence and the modesty of the effect are theoretically coherent. FoMO primarily reflects the frustration of relatedness needs (Przybylski et al., 2013), and the positive association indicates that first year students who are more anxious about missing their peers' experiences tend to compensate by monitoring and sharing social content during lectures (Kardefelt-Winther, 2014). SDT, however, specifies three basic needs, and cyberslacking may also arise from the frustration of the other two. Lectures experienced as controlling or unengaging may frustrate autonomy, and dense health sciences content may frustrate competence and induce cognitive overload; in both cases students may turn to online content to escape boredom or strain rather than to relieve social anxiety. The account of medical students' cyberslacking in which low autonomy, stress and fatigue, and unengaging lectures emerged as central triggers (Zhou et al., 2025) supports this broader reading. FoMO should therefore be understood as indexing the relatedness pathway to cyberslacking, which is only one of several need based pathways, and this consideration helps to explain why it accounts for a small share of the variance.

The sensitivity indices speak directly to the question of whether the FoMO effect reflects motivation or merely exposure. Daily device use differed noticeably across study programs, from 5.50 hours among Nursing students to 7.46 hours among Medicine students (Table 1), and heavier device use is plausibly related to both FoMO and the opportunity to cyberslack (Gökçearslan et al., 2016). Correlations of about .25 between indicators of device or social media use and FoMO fall within the range reported in meta analytic work (Akbari et al., 2021; Fioravanti et al., 2021), so confounding by exposure of the strength required to overturn the inference cannot be ruled out. Device use and study program were recorded to describe the sample rather than as part of the a priori model, and adjusting for them post hoc would have consumed five of the available degrees of freedom, estimated program contrasts from groups as small as 10 students, and raised the smallest detectable effect to f^2 = .11, which exceeds the effect observed here. Reporting the confounding threshold is therefore a more transparent alternative, because it states precisely how strong an omitted variable must be to explain away the FoMO effect and provides a benchmark against which future studies that measure exposure objectively can be evaluated. The prudent reading is that FoMO is associated with cyberslacking beyond chance, but that its unique contribution net of exposure remains to be established.

Several further alternative explanations and limitations qualify these conclusions. First, the cross sectional design precludes causal inference, and the direction of influence may be reciprocal, because frequent cyberslacking exposes students to a continuous stream of their peers' activities, which may itself heighten FoMO. Second, both constructs were measured by self report at the same time point, so common method variance may have inflated, and social desirability may have deflated, the observed association. Third, the sample was small, recruited purposively from a single faculty, and dominated by psychology students, which limits generalizability; the sensitivity power analysis also showed that the design was adequately powered only for effects slightly larger than the one observed, as reflected in the wide confidence interval. Fourth, daily device use was captured with a single self reported item, and the normality of residuals was inferred from the distributions of the observed variables rather than examined directly. Finally, theoretically relevant moderators and mediators were not measured. Self regulation and classroom norms regarding device use may determine when FoMO is converted into cyberslacking, and compulsive social media use may transmit its effect (Li & Liu, 2022; Ningrum & Pratisti, 2026; Taneja et al., 2015). Because these constructs were outside the scope of the present dataset, the study cannot test the mechanism it proposes. Future research should therefore test a moderated mediation model in which FoMO predicts cyberslacking through compulsive social media use, with the indirect path conditional on self regulation and classroom device norms, preferably using longitudinal or experience sampling designs combined with objective measures of device activity.

The practical implications should be framed in proportion to these findings. Because FoMO explained only a small portion of the variance, the results do not justify an institutional policy built around FoMO alone. Digital literacy activities that help students recognize and manage the urge to remain socially connected may be a useful component of student support at FKIK Universitas Jambi, particularly during the first year, but they should be combined with other measures that the literature identifies as relevant, such as training in self regulation and attention management, instructional designs that increase active engagement and support autonomy during lectures, and clear, jointly agreed norms on device use in the classroom (Taneja et al., 2015;

Zhou et al., 2025). Any such program should be evaluated empirically before it is adopted more widely, and its expected benefits should be estimated realistically in light of the modest effect observed here.

Conclusions

This study shows that fear of missing out is a statistically significant but modest predictor of cyberslacking among first year students of a faculty of medicine and health sciences in Indonesia. Students who were more anxious about missing their peers' experiences tended to engage more often in nonacademic online activity during lectures, a pattern consistent with the relatedness pathway derived a priori from Self Determination Theory. Yet FoMO explained less than one tenth of the differences in cyberslacking, and sensitivity analyses showed that the inference would not survive an omitted confounder, such as device exposure, of moderate strength. The study thus extends previous bivariate findings by quantifying the robustness of the FoMO effect to omitted confounding, by calibrating its magnitude against meta analytic and individual differences benchmarks, and by offering a need based explanation of why cyberslacking in this population is best understood as a multicausal behavior in which FoMO plays a limited role. Efforts to reduce cyberslacking should treat FoMO oriented digital literacy as one of several complementary strategies rather than as the primary solution, and future studies should measure device exposure objectively and test self regulation, classroom device norms, and compulsive social media use as covariates, moderators, and mediators in larger, more diverse, and longitudinal samples.

References

Akbari, M., Seydavi, M., Palmieri, S., Mansueto, G., Caselli, G., & Spada, M. M. (2021). Fear of missing out (FoMO) and internet use: A comprehensive systematic review and meta-analysis. *Journal of Behavioral Addictions, 10*(4), 879–900. https://doi.org/10.1556/2006.2021.00083

Akbulut, Y., Dursun, Ö. Ö., Dönmez, O., & Şahin, Y. L. (2016). In search of a measure to investigate cyberloafing in educational settings. *Computers in Human Behavior, 55*, 616–625. https://doi.org/10.1016/j.chb.2015.11.002

Alt, D. (2015). College students' academic motivation, media engagement and fear of missing out. *Computers in Human Behavior, 49*, 111–119. https://doi.org/10.1016/j.chb.2015.02.057

Alt, D. (2017). Students' social media engagement and fear of missing out (FoMO) in a diverse classroom. *Journal of Computing in Higher Education, 29*(2), 388–410. https://doi.org/10.1007/s12528-017-9149-x

Alvaridzi, R. A. D., & Ardelia, V. (2025). Dilema mahasiswa di era digital: Korelasi antara FoMO dan cyberslacking. *Character: Jurnal Penelitian Psikologi, 12*(1).

Asosiasi Penyelenggara Jasa Internet Indonesia. (2024). *Laporan survei penetrasi internet Indonesia 2024*. APJII.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry, 11*(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01

Elhai, J. D., Yang, H., & Montag, C. (2021). Fear of missing out (FOMO): Overview, theoretical underpinnings, and literature review on relations with severity of negative affectivity and problematic technology use. *Brazilian Journal of Psychiatry, 43*(2), 203–209. https://doi.org/10.1590/1516-4446-2020-0870

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

Fioravanti, G., Casale, S., Bocci Benucci, S., Prostamo, A., Falone, A., Ricca, V., & Rotella, F. (2021). Fear of missing out and social networking sites use and abuse: A meta-analysis. *Computers in Human Behavior, 122*, 106839. https://doi.org/10.1016/j.chb.2021.106839

Frank, K. A. (2000). Impact of a confounding variable on a regression coefficient. *Sociological Methods & Research, 29*(2), 147–194. https://doi.org/10.1177/0049124100029002001

Frank, K. A., Maroulis, S. J., Duong, M. Q., & Kelcey, B. M. (2013). What would it take to change an inference? Using Rubin's causal model to interpret the robustness of causal inferences. *Educational Evaluation and Policy Analysis, 35*(4), 437–460. https://doi.org/10.3102/0162373713493129

Funder, D. C., & Ozer, D. J. (2019). Evaluating effect size in psychological research: Sense and nonsense. *Advances in Methods and Practices in Psychological Science, 2*(2), 156–168. https://doi.org/10.1177/2515245919847202

Gignac, G. E., & Szodorai, E. T. (2016). Effect size guidelines for individual differences researchers. *Personality and Individual Differences, 102*, 74–78. https://doi.org/10.1016/j.paid.2016.06.069

Gökçearslan, Ş., Mumcu, F. K., Haşlaman, T., & Çevik, Y. D. (2016). Modelling smartphone addiction: The role of smartphone usage, self-regulation, general self-efficacy and cyberloafing in university students. *Computers in Human Behavior, 63*, 639–649. https://doi.org/10.1016/j.chb.2016.05.091

Junco, R. (2012). In-class multitasking and academic performance. *Computers in Human Behavior, 28*(6), 2236–2243. https://doi.org/10.1016/j.chb.2012.06.031

Kardefelt-Winther, D. (2014). A conceptual and methodological critique of internet addiction research: Towards a model of compensatory internet use. *Computers in Human Behavior, 31*, 351–354. https://doi.org/10.1016/j.chb.2013.10.059

Kurniawan, R., & Utami, R. H. (2022). Validation of Online Fear of Missing Out (ON-FoMO) scale in Indonesian version. *Jurnal Neo Konseling, 4*(3). https://doi.org/10.24036/00651kons2022

Li, X., & Liu, D. (2022). The influence of technostress on cyberslacking of college students in technology-enhanced learning: Mediating effects of deficient self-control and burnout. *International Journal of Environmental Research and Public Health, 19*(18), 11800. https://doi.org/10.3390/ijerph191811800

McKee, P. C., Budnick, C. J., Walters, K. S., & Antonios, I. (2022). College student Fear of Missing Out (FoMO) and maladaptive behavior: Traditional statistical modeling and predictive analysis using machine learning. *PLOS ONE, 17*(10), e0274698. https://doi.org/10.1371/journal.pone.0274698

Mercado, B. K., Giordano, C., & Dilchert, S. (2017). A meta-analytic investigation of cyberloafing. *Career Development International, 22*(5), 546–564. https://doi.org/10.1108/CDI-08-2017-0142

Ningrum, D. S., & Pratisti, W. D. (2026). Self-regulation sebagai mediator hubungan loneliness dan fear of missing out dengan perilaku cyberslacking mahasiswa. *Jurnal Psikologi, 22*(1), 10–22. https://doi.org/10.24014/psikologi.v22i1.32764

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Periantalo, J. (2019). *Penelitian kuantitatif untuk psikologi*. Pustaka Pelajar.

Przybylski, A. K., Murayama, K., DeHaan, C. R., & Gladwell, V. (2013). Motivational, emotional, and behavioral correlates of fear of missing out. *Computers in Human Behavior, 29*(4), 1841–1848. https://doi.org/10.1016/j.chb.2013.02.014

Ravizza, S. M., Uitvlugt, M. G., & Fenn, K. M. (2017). Logged in and zoned out: How laptop internet use relates to classroom learning. *Psychological Science, 28*(2), 171–180. https://doi.org/10.1177/0956797616677314

Rozgonjuk, D., Elhai, J. D., Ryan, T., & Scott, G. G. (2019). Fear of missing out is associated with disrupted activities from receiving smartphone notifications and surface learning in college students. *Computers & Education, 140*, 103590. https://doi.org/10.1016/j.compedu.2019.05.016

Sette, C. P., Lima, N. R. S., Queluz, F. N. F. R., Ferrari, B. L., & Hauck, N. (2020). The Online Fear of Missing Out Inventory (ON-FoMO): Development and validation of a new tool. *Journal of Technology in Behavioral Science, 5*(1), 20–29. https://doi.org/10.1007/s41347-019-00110-0

Simanjuntak, E., Fajrianthi, F., & Purwono, U. (2019). Skala cyberslacking pada mahasiswa. *Jurnal Psikologi, 18*(1), 55–68. https://doi.org/10.14710/jp.18.1.55-68

Tabachnick, B. G., & Fidell, L. S. (2019). *Using multivariate statistics* (7th ed.). Pearson.

Tandon, A., Dhir, A., Almugren, I., AlNemer, G. N., & Mäntymäki, M. (2021). Fear of missing out (FoMO) among social media users: A systematic literature review, synthesis and framework for future research. *Internet Research, 31*(3), 782–821. https://doi.org/10.1108/INTR-11-2019-0455

Taneja, A., Fiore, V., & Fischer, B. (2015). Cyber-slacking in the classroom: Potential for digital distraction in the new age. *Computers & Education, 82*, 141–151. https://doi.org/10.1016/j.compedu.2014.11.009

Williams, M. N., Grajales, C. A. G., & Kurkiewicz, D. (2013). Assumptions of multiple regression: Correcting two misconceptions. *Practical Assessment, Research & Evaluation, 18*, Article 11.

Wu, J., Mei, W., & Ugrin, J. C. (2018). Student cyberloafing in and out of the classroom in China and the relationship with student performance. *Cyberpsychology, Behavior, and Social Networking, 21*(3), 199–204. https://doi.org/10.1089/cyber.2017.0397

Zamzani, S., Ahmad, & Ahkam, M. (2024). Hubungan regulasi diri dengan cyberslacking pada mahasiswa di Universitas Negeri Makassar. *Pinisi Journal of Art, Humanity & Social Studies, 4*(2), 26–34.

Zhou, J., Jin, L., & Hu, Y. (2025). From distraction to addiction? Understanding academic cyberslacking as a behavioral dependency among medical students. *Frontiers in Psychology, 16*, 1592370. https://doi.org/10.3389/fpsyg.2025.1592370