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Problematic smartphone use and academic achievement: A systematic review and meta-analysis

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META-ANALYSES

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ABSTRACT

Background and aims: The present study aimed to synthesize existing quantitative evidence on the relationship between problematic smartphone use (PSU) and academic achievement with a focus on quantifying its magnitude and examining its potential moderators. *Methods:* Eligible studies were searched for up to February 10, 2023 in six different databases (i.e., *MEDLINE, Current Contents Connect, PsycINFO, Web of Science, SciELO,* and *Dissertations & Theses Global*). Studies were considered eligible if they provided information derived from self-report instruments that allowed statistical calculation of the relationship between PSU and academic achievement. Pooled effect sizes (r) were computed using a random-effects model. Meta-regressions were conducted to test the influence of study-level moderators on the relationship of interest. Influence analyses and a three-parameter selection model (3PSM) were conducted to examine the robustness of the results and publication bias, respectively. *Results:* A total of 33 effect sizes from 29 studies (n = 48,490) were retrieved. Results showed a small effect size ($r = -0.110$), which tended to be larger in samples consisting of students from elementary and middle schools. *Discussion and Conclusions:* Findings from the present study contribute to the understanding of a potential determinant of decreased academic achievement by providing evidence that PSU may be one of them.

KEYWORDS

human-computer interface, media in education, problematic smartphone use; smartphone dependence, smartphone addiction

INTRODUCTION

The widespread availability of smartphones has facilitated immediate access to information, entertainment, and remote social interaction (O'Dea, 2023; Sarwar & Soomro, 2013; Scott, Valley, & Simecka, 2016). One research topic that has attracted a great deal of attention in parallel to the growing popularity of smartphones is the potential problematic nature of their use (Csibi, Griffiths, Demetrovics, & Szabo, 2021; Harris, Regan, Schueler, & Fields, 2020). In this context, the term 'problematic smartphone use' (PSU) has been proposed to refer to a multidimensional behavioral pattern involving both psychological symptoms (e.g., salience and loss of control) and physical symptoms (e.g., tolerance and withdrawal), that may result

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in negative consequences in daily life (Billieux, 2012; Pontes, Kuss, & Griffiths, 2015). Such consequences include a number of health issues such as headaches, sleep disturbances, gastrointestinal and musculoskeletal problems, anxiety/depressive symptoms (Ratan, Parrish, Zaman, Alotaibi, & Hosseinzadeh, 2021; Reer, Wehden, Janzik, & Quandt, 2022; Yang, Fu, Liao, & Li, 2020), increased risk of traffic and pedestrian accidents (Rosenthal, Li, & Gately, 2022; Rosenthal, Li, Wensley, Perez, & Gately, 2022), decreased job performance (Alan, Ozen Bekar, & Güngör, 2022), and attentional and learning impairments in educational settings (Dontre, 2021; Kates, Wu, & Coryn, 2018; Yang, Asbury, & Griffiths, 2021).

Academic achievement is an indicator not only of students' learning status but also of long-term health (Lê-Scherban, Diez Roux, Li, & Morgenstern, 2014) and future professional success (French, Homer, Popovici, & Robins, 2015). More recently, PSU has been a subject of research interest in relation to decreased academic achievement (Amez & Baert, 2020; Kates et al., 2018). The potential negative causal relationship between PSU and academic achievement has been theoretically justified on the basis (i) of the trade-off (in terms of time spent) between smartphone use and study activities; and (ii) that constant switching between study-related activities and social activities on the smartphone can lead to cognitive overload, inefficiency, lack of attention/concentration, and inability to exert prolonged mental effort, consequences that can prevent students from performing well in their academic studies (Aru & Rozgonjuk, 2022; Baert et al., 2020; Dontre, 2021). The theoretical assumption concerning the negative relationship between PSU and academic achievement have received some support in the literature. Indeed, the findings of meta-analytic research has reported a small-sized negative relationship between both variables (i.e., $r = -0.12$) (Kates et al., 2018). However, this meta-analysis was not without important limitations. First, the results concerning PSU were derived from a subgroup analysis conducted in the context of examining smartphone use variables that are not necessarily related to functional impairment or harm (e.g., number of hours or frequency of use), and therefore not necessarily problematic (Billieux, Maurage, Lopez-Fernandez, Kuss, & Griffiths, 2015). This implies that the search performed by the authors did not include relevant terms in the field of PSU research (e.g., problematic smartphone use, smartphone dependence, or smartphone addiction) (Harris et al., 2020; Yang et al., 2020). Therefore, it is highly likely that relevant data from eligible research was not retrieved for analysis.

Second, an important limitation resulted from the very limited number of effect sizes included in the meta-analysis (i.e., $k = 7$) (Kates et al., 2018). This issue precluded examining whether – as occurs with some other potential predictors of academic achievement (e.g., sport participation, socioeconomic status, or personality) – the relationship of interest was moderated by other variables either of a methodological nature (e.g., the way of assessing either the predictor variable or academic achievement) (Liu, Peng, & Luo, 2020; Owen et al., 2022) or sociodemographic nature (e.g., education level or sex) (Mammadov, 2022). Taken together, these limitations call into question the accuracy of the summarized value of the relationship between PSU and academic performance that is currently available (Kates et al., 2018).

Quantifying the relationship between PSU and academic achievement by incorporating new data available since the publication of the only previous meta-analytic study, while addressing the aforementioned limitations, may provide greater insight regarding the reasons underlying the variability in size and direction reported in the literature for this relationship (Bai, Chen, & Han, 2020; Domoff, Foley, & Ferkel, 2020; Przepiorka, Błachnio, Cudo, & Kot, 2021; Rathakrishnan et al., 2021; Zhou, Liu, Wang, Liu, & Li, 2022). Similarly, identifying populations that may be particularly susceptible in terms of showing a negative impact on their academic achievement due to experiencing high PSU levels could be useful in defining priority targets of intervention actions that, focusing on PSU reduction (Olson, Sandra, Chmoulevitch, Raz, & Veissière, 2022; Precht et al., 2024), may have the potential to contribute to maximizing students' current academic performance and, by extension, their future career development and psychological well-being (French et al., 2015; Lê-Scherban et al., 2014).

In view of the aforementioned considerations, the present study aimed to synthesize existing quantitative evidence on the relationship between PSU and academic achievement with a focus on two objectives. First, to quantify the magnitude of such a relationship. Second, to explanatorily examine whether the relationship between PSU and academic achievement might be moderated by the different methodological and socio-demographic variables emerging from the analysis of the common features of the studies, providing data on the relationship of interest.

MATERIAL AND METHODS

The present study was conducted following the PRISMA statement (Page et al., 2021) (see Supplementary material A).

Locating studies

The following six databases were searched for potentially eligible studies (February 10, 2023): *MEDLINE, Current Contents Connect, PsycINFO, Web of Science, SciELO,* and *Dissertations & Theses Global* (see Supplementary material B) using the following search terms: ("academic achievement" OR "academic performance" OR "academic outcome" OR "academic success" OR "academic competence" OR "academic attainment" OR "academic improvement" OR "school performance" OR "school outcome" OR "school achievement" OR "scholastic achievement" OR "education outcome" OR "education achievement" OR "education attainment" OR "education improvement" OR "education performance" OR "student achievement" OR "student competence" OR "student attainment" OR "student improvement" OR "student outcome" OR "student performance" OR "performance level" OR "learning outcome" OR "learning attainment" OR "learning achievement" OR "learning performance" OR "achievement gain") AND (addiction OR overuse OR "problematic use" OR problematic OR "excessive use" OR excessive OR dependence OR compulsive) AND ("mobile phone" OR smartphone OR "smart phone" OR cellphone OR "cell phone"). Manual searches of the reference lists of the retrieved studies were also carried out in the search for others that might also be eligible.

Endnote X9 software was used for reference management and duplicate elimination at the screening stage. Inter-coder reliability (Freelon, 2013) was 0.95 (percent agreement: 98.4%) for the abstract/title, and 0.89 (percent agreement: 95.2%) for the full text. The first and the second author separately selected the studies by sequential examination of (a) their titles/abstracts, and (b) their full-texts. Where duplicated data occurred – typically due to being from a doctoral thesis – only the data from peer-reviewed publications were used. Disagreements were discussed among the authors until consensus was reached.

Eligibility criteria

The present study collated data on the association between PSU and academic achievement. For the purpose of minimizing publication bias, the aim of the literature search was to retrieve data from both published and unpublished studies.

Inclusion criteria. Studies were considered eligible if they met the following criteria: (i) at least one academic achievement score was provided; (ii) at least one PSU score derived from a psychometrically-validated self-report instrument (i.e., the scale used had psychometric properties that were formally tested in a peer-reviewed paper) either on a continuum (i.e., the greater the score, the greater the risk) or dichotomous scoring (i.e., being considered as being at-risk or not at-risk) was provided, (iii) studies were published in English or Spanish (the languages spoken by the authors), although no restrictions were set in terms of country of origin; and (iv) there were sufficient data available to calculate the effect sizes of interest.

Exclusion criteria. To facilitate the replicability of the present meta-analysis, primary studies were excluded if: (i) the PSU scores were obtained using versions of the instruments that presented factor structures that differed from those originally proposed, which may therefore differ from the original one in terms of construct validity; (ii) isolated items assessing a multidimensional and complex phenomenon such as PSU (Billieux, 2012; Pontes et al., 2015) were used, since this may compromise the comprehensiveness of the construct; (iii) composite scores of PSU were obtained by merging several validated psychometric scales assessing PSU but not scores derived from single instruments were used, since this would imply assuming as acceptable a factor structure which has not been previously tested; and (iv) the study sample consisted of less than 30 participants. The latter was because of the increased likelihood in both sampling error and variations in the assessment of heterogeneity which results from including studies with small sample sizes (Lin, 2018).

Coding procedure

A coding framework was developed and pilot-tested in view of the common features of the studies retrieved in a preliminary search. The resulting coding sheet was used by the first and the second authors of the present study when extracting the relevant data from the retrieved studies (see Supplementary material C). Disagreements between both reviewers were discussed until consensus was reached. The following coding categories were considered: (a) citation and year of publication, (b) sample size, (c) sex, (d) age, (e) region (geographic location), (f) PSU measure, (g) PSU assessment (i.e., continuous or categorical), (h) academic achievement indicator, (i) educational level, (j) publication status, (k) study quality, and (l) effect size of the correlation between PSU and academic achievement. These coded features were considered for descriptive purposes as well as candidate moderator variables where appropriate (Rosenthal, 1995).

Risk of bias

Risk of bias was assessed using the Newcastle-Ottawa Scale (NOS) for evaluating cross-sectional/survey studies (Hillen, Medendorp, Daams, & Smets, 2017). This instrument allows for the calculation of a score from 0 to 16 for each of the following components: (a) clarity of stated aim, (b) sample representativeness, (c) sample size, (d) non-respondents, (e) ascertainment of the exposure, (f) control of confounding factors, (g) comparability of participants across outcome groups, (h) assessment of the outcome, and (i) statistical tests. High scores on the NOS suggest a decreased risk of bias. The risk of bias assessment was independently conducted by the first and second authors. Disagreements between the two reviewers were discussed and resolved on a consensual basis. As a result of this procedure, scores between 7 and 12 in terms of risk of bias were assigned for the 29 retrieved studies.

Statistical analysis

The primary effect size index used in the present meta-analysis was the Pearson product-moment correlation coefficient (r) with 95% confidence interval (CI). Estimated effect sizes were r-to-z transformed before conducting statistical analyses. To facilitate interpretation of the results, effect sizes were subsequently z-to-r transformed (Borenstein, Hedges, Higgins, & Rothstein, 2009).

The pooled effect sizes were computed using a random-effects model (Pigott, 2012). This approach was adopted on the premise that: (i) heterogeneity between studies in terms of participants' characteristics such as sex or age and exposure/outcomes was expected, and (ii) variations in the distribution and sampling errors of effect sizes may account for the differences between them (Mueller et al., 2018). Statistical heterogeneity was expressed using the I^2 statistic, with values of 25%, 50%, and 75% interpreted as low, moderate, and high heterogeneity, respectively (Higgins, Thompson, Deeks, & Altman, 2003). The robustness of the results was examined using graphic display of studies heterogeneity (GOSH) plot analysis. This procedure involved the following three steps: (i) fitting both k models and all 2^{k-1} possible study combinations by employing three cluster algorithms (i.e., k-means, density-based spatial clustering of applications with noise, and Gaussian mixture models), (ii) obtaining a plot in which the pooled effect size and the between-study heterogeneity are respectively displayed on the x- and on y-axis (Olkin, Dahabreh, & Trikalinos, 2012), and (iii) employing Cook's distance values for the purpose of identifying likely influential studies (i.e., potential outliers) within the context of the clusters emerging in the first step (Harrer, Cuijpers, Furukawa, & Ebert, 2021).

Provided that at least 10 effect sizes were available, continuous covariates such as age, percentage of females, year of publication, and study quality, and categorical variables such as sex, region, PSU assessment, academic achievement indicator, educational level, and publication status were evaluated as potential sources of variance in heterogeneity using a mixed-effects model (Fu et al., 2011). Categorical variables were transformed into dummy variables. Both univariable (i.e., those considering each potential moderator in isolation) and multivariable (i.e., those including all significant moderators identified in the first stage) regression models were conducted. The variance explained by the moderators was expressed as a percentage (R^2). Publication bias was examined using two methodological approaches. First, visual inspection of the symmetry of a contour-enhanced funnel plot (Peters, Sutton, Jones, Abrams, & Rushton, 2008). Second, a three-parameter selection model (3PSM) involving a simple model with a single cut-off point (<0.05) and no moderators was employed for examining publication bias. Statistically significant results of the likelihood-ratio test comparing unadjusted and adjusted meta-analytic models derived from the 3PSM procedure suggest that the latter should be retained, which supports the presence of publication bias (Coburn & Vevea, 2019). The 3PSM has been recommended over other available methodological approaches in the examination of publication bias when, as in the present case, high levels of heterogeneity are expected (Carter, Schönbrodt, Gervais, & Hilgard, 2019).

Point mean estimates of effect sizes were interpreted as very small (0.00–0.10), small (0.10–0.20), medium (0.20–0.30), large (0.30–0.40), and very large (>0.40) (Funder & Ozer, 2019). The statistical analyses described in this section were carried out using R (version 4.2.2). Random-effects models were estimated using an estimation method that, such as maximum likelihood (REML), is expected to be largely robust to the absence of normal data distributions (Langan et al., 2019).

The dependence generated by considering multiple effect sizes derived from the same sample (Becker, 2000; Hedges, 2009) was treated as follows. First, when there were multiple dependent effects obtained from different PSU measures in one study (e.g., Olufadi, 2015), random removal of effect sizes was conducted until just one effect size remained (Cheung, 2014). Secondly, the different effect sizes reported for various population groups in the same study (e.g., males/females), were treated individually (Cheung, 2014).

RESULTS

Description of studies

A total of 792 outputs were initially identified. As a result of the study selection procedure (see Fig. 1), 29 primary cross-sectional studies involving 33 effect sizes (N = 48,490) published between 2015 and 2022, were included in the systematic review and meta-analysis. The main characteristics of the retrieved studies can be found in Table 1. Twenty-seven of the studies included in the meta-analyses were published peer-reviewed papers and two were doctoral dissertations or conference proceedings. Academic achievement was expressed in terms of grade point average or GPA ($K = 24$), self-reported grades ($K = 3$) or test scores ($K = 6$). From the retrieved studies, 22 were conducted in non-Western regions ($K = 24$), five were conducted in Western regions ($K = 8$), and one did not report this information ($K = 1$). The studies included in the meta-analysis consisted of samples of students attending tertiary education (all attending college/university) ($K = 18$), high school ($K = 9$), elementary/middle school ($K = 5$), and both elementary/middle school and high school ($K = 1$). The mean age of the samples under analysis ranged from 10.00 years to 23.78 years (M_{age} = 17.78 years, SD_{age} = 4.49).

PSU and academic achievement

Findings from the random-effects model (see Fig. 2) showed a negative small-sized effect ($r = -0.110$, $p < 0.001$; 95% CI = -0.156 to -0.066, $I^2 = 93.70$). Findings from the univariate meta-regression analysis for categorical variables (see Table 2) indicated that educational level was the only significant moderator of the relationship under consideration (omnibus-test [3, 29] = 3.327; $p = 0.033$; $R^2 = 21.80$), this being stronger among samples from elementary/middle school students. Since only one potential moderator variable emerged, multivariable meta-regression analysis was not carried out.

Sensitivity analysis and publication bias

After removing four effect sizes from four studies (Bai et al., 2020; Domoff et al., 2020; Zhou, Liu, Wang, et al., 2022; Zhou, Liu, Ye, et al., 2022) identified as potential outliers according to the results of influence analyses (see Supplementary material D), the result from the adjusted model ($r = -0.123$, $p < 0.001$; 95% CI = -0.164 to -0.081; $I^2 = 83.50$) was found to be largely consistent with the non-

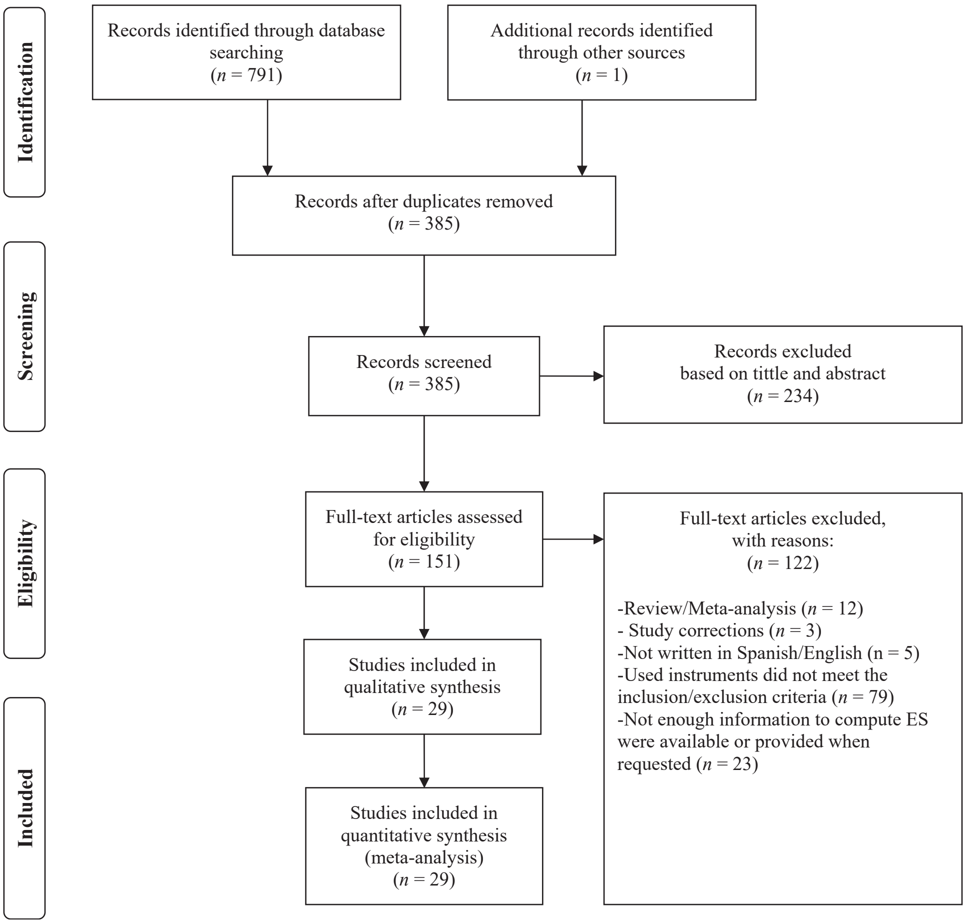

Fig. 1. PRISMA flow diagram of study

adjusted one ($r = -0.110$, $p < 0.001$; 95% CI $= -0.156$ to -0.066, $I^2 = 93.70$). Examination of the symmetry of the funnel plot yielded no evidence of publication bias (see Supplementary material E). The results of 3PSM did not suggest the presence of publication bias [$\chi^2(1) = 0.034$, $p = 0.854$].

DISCUSSION

By identifying data from 29 studies and conducting further analysis of 33 effect sizes involving 48,490 participants, the present systemic review and meta-analysis provides a comprehensive evidence-based assessment of the relationship between PSU and academic achievement. Findings showed a negative and small-sized relationship between the two variables of interest, which tended to be stronger (i.e., medium-sized) among samples consisting of elementary/middle school students. Conversely, the relationship PSU and academic achievement was not found to differ across sex, nor to depend on variables such as age, year of publication, study quality, academic achievement indicator, PSU assessment or geographical region. These findings extend meta-analytic evidence supporting the potential detrimental effects of PSU (Alan et al., 2022; Ratan et al., 2021; Reer et al., 2022; Rosenthal, Li, & Gately, 2022; Rosenthal, Li, Wensley, et al., 2022; Yang et al., 2020) by demonstrating that a negative small-sized and consistent relationship exists between PSU and academic achievement. The main implications derived from the results obtained are set out in more detail below.

Overall effects

The magnitude of the relationship between PSU and academic achievement found in the present study is consistent with that reported in a previous meta-analytic study (Kates et al., 2018) which included notably fewer effect sizes than those considered here (i.e., $K = 33$ vs. $K = 7$). In addition, a comparison of the overall value found here with those reported in previous meta-analytic studies for other plausible antecedents of academic achievement allow for a twofold conclusion to be made concerning the strength of the relationship between academic achievement and PSU. First, that it appears to be largely equivalent (although opposite in sign) to those reported for personality factors such as openness (i.e., to be creative and open-minded) (Mammadov, 2022), health behaviors such as sport participation (Owen et al., 2022), health indicators such as sleep quality (Musshafen et al., 2021), or experiences gained from the teaching-learning processes such as interacting positively with classmates (Wentzel, Jablansky, & Scalise, 2018) or

Table 1. Studies' characteristics and effect size

Study	*N*	Sex	Percentage of females	Age	Region	Educational level	Academic achievement indicator	PSU measure	PSU assessment	Publication status	Quality	ES (*r*)
Alinejad, Parizad, Yarmohammadi, and Radfar (2022)	447	Both	62%	23.78	Non-Western	Tertiary (College)	Test scores	SAS-SV	Continuous	Published	9	−0.171
Alotaibi, Fox, Coman, Ratan, and Hosseinzadeh (2022)	545	Both	55%	N.A.	Non-Western	Tertiary (College)	GPA	SAS-SV	Categorical	Published	8	−0.166
Al-Shahrani (2020)	188	Male	0%	N.A.	Non-Western	Tertiary (College)	GPA	PUMP	Continuous	Published	9	−0.210
Bai et al. (2020)	1,794	Both	49%	12.6	Non-Western	Elementary/Middle School and High School	GPA	MPAI	Continuous	Published	9	0.128
Buctot et al. (2021)	3,374	Both	58%	14.76	Non-Western	High School	Self-report grades	SAS-SV	Continuous	Published	8	−0.030
Coskun and Karayagız Muslu (2019)	1,630	Both	45%	N.A.	Non-Western	High School	GPA	PMPUQ	Continuous	Published	8	−0.280
Domoff et al. (2020)	641	Both	54%	N.A.	Western	High School	Self-report grades	APUS	Continuous	Published	9	0.170
Eksi, Demirci, and Tanyeri (2020)	337	Both	50%	15.76	Non-Western	High School	GPA	SABAS	Categorical	Published	7	−0.215
Eoh et al. (2022)	695	Both	49%	10.32	Non-Western	Elementary/Middle School	Test scores	IADS	Continuous	Published	8	−0.180
Fernández-Andújar, Alonso, Sorribes, Villalba, and Calderon (2022)	715	Both	82%	22.1	Western	Tertiary (College)	GPA	SABAS	Continuous	Published	8	0.021
Garakouei, Mousavi, Rezaei, and Lafmejani (2020)	330	Both	48%	16.42	Non-Western	High School	GPA	COS	Continuous	Published	8	−0.211
Hawi and Samaha (2016; Female)	114	Female	100%	N.A.	Non-Western	Tertiary (College)	GPA	SAS-SV	Categorical	Published	9	0.151
Hawi and Samaha (2016; Male)	135	Male	0%	N.A.	Non-Western	Tertiary (College)	GPA	SAS-SV	Categorical	Published	9	−0.160
Hilt (2019)	126	Both	60%	14.82	Non-Western	High School	GPA	TMD	Continuous	Published	8	−0.207
Ibrahim et al. (2018)	610	Both	82%	21.6	Non-Western	Tertiary (College)	GPA	PMPUQ	Continuous	Published	11	−0.074
Kemp Jr. (2018)	122	Both	57%	N.A.	Western	Tertiary (College)	GPA	SAS-SV	Continuous	Unpublished	9	−0.072
Lee, Cho, Kim, and Noh (2015)	210	Female	100%	22	Non-Western	Tertiary (College)	Test scores	SAL	Categorical	Published	9	−0.172
Olufadi (2015)	286	Both	52%	21	Non-Western	Tertiary (College)	GPA	MPUS	Continuous	Published	7	−0.071

(continued)

Table 1. Continued

Study	*N*	Sex	Percentage of females	Age	Region	Educational level	Academic achievement indicator	PSU measure	PSU assessment	Publication status	Quality	ES (*r*)
Panek, Khang, Liu, and Chae (2018; Korean)	241	Both	65%	21.25	Non-Western	Tertiary (College)	Test scores	MPPUS	Continuous	Published	9	0.080
Panek et al. (2018; U.S.)	222	Both	NA	N.A.	Western	Tertiary (College)	GPA	MPPUS	Continuous	Published	9	−0.020
Pathak and Mhaske (2019)	441	Both	51%	19.33	Non-Western	Tertiary (College)	GPA	PUMP	Continuous	Published	8	−0.093
Przepiorka et al. (2021; Boys)	209	Male	0%	N.A.	Western	Elementary/Middle School	GPA	SAS-SV	Continuous	Published	10	−0.200
Przepiorka et al. (2021; Girls)	218	Female	100%	N.A.	Western	Elementary/Middle School	GPA	SAS-SV	Continuous	Published	10	−0.260
Rathakrishnan et al. (2021)	323	Both	50%	N.A.	Non-Western	Tertiary (College)	GPA	SAS-SV	Continuous	Published	8	−0.340
Samaha and Hawi (2016)	293	Both	46%	20.96	Unknown	Tertiary (College)	GPA	SAS-SV	Continuous	Published	9	−0.143
Sert, Taskin Yilmaz, Karakoc Kumsar, and Aygin (2019)	743	Both	60%	20.93	Non-Western	Tertiary (College)	GPA	PMPUS	Continuous	Published	9	0.047
Spiratos (2021)	319	Both	57%	N.A.	Western	High School	GPA	SAS-SV	Continuous	Unpublished	9	−0.050
Winskel, Kim, Kardash, and Belic (2019; Australian)	270	Both	78%	21.26	Western	Tertiary (College)	GPA	SAS-SV	Continuous	Published	10	−0.100
Winskel et al. (2019; Korean)	119	Both	50%	20.64	Non-Western	Tertiary (College)	GPA	SAS-SV	Continuous	Published	10	−0.120
Wu and Siu (2020)	411	Both	48%	N.A.	Non-Western	High School	Self-report grades	PCPU-Q	Categorical	Published	9	−0.134
Yadav, Kodi, and Deol (2021)	285	Both	26%	16.15	Non-Western	High School	GPA	TMD	Continuous	Published	10	−0.125
Zhou, Liu, Wang, Liu, and Li (2022)	12,252	Both	49%	10	Non-Western	Elementary/Middle School	Test scores	PSU	Continuous	Published	12	−0.212
Zhou, Liu, Ye, et al. (2022)	19,845	Both	48%	10	Non-Western	Elementary/Middle School	Test scores	PSU	Continuous	Published	12	−0.210

Note. GPA = Grade Point Average; PSU = Problematic smartphone use; SAS-SV = Smartphone Addiction Scale-Short Version; PUMP = Problematic Use of Mobile Phones; MPAI = Mobile Phone Addiction Index; PMPUQ = Problematic Mobile Phone Use Questionnaire; APU = Addictive Patterns of Use Scale; SABAS = Smartphone Application-Based Addiction Scale; IADS = Internet Addiction Diagnostic Scale (adapted to smartphone); COS = Cell-Phone Over-Use Scale; TMD = Test of Mobile Dependence; SAL = Smartphone Addiction Level; MPUS = Mobile Phone Usage Scale (Addiction subscale); MPPUS = Mobile Phone Problem Use Scale, PUMP = Problematic Use of Mobile Phones Scale; PMPUS = Problematic Mobile Phone Use Scale; PCPU-Q ES = Problematic Cellular Phone Use Questionnaire; ES = Effect size; N.A. = Not available.

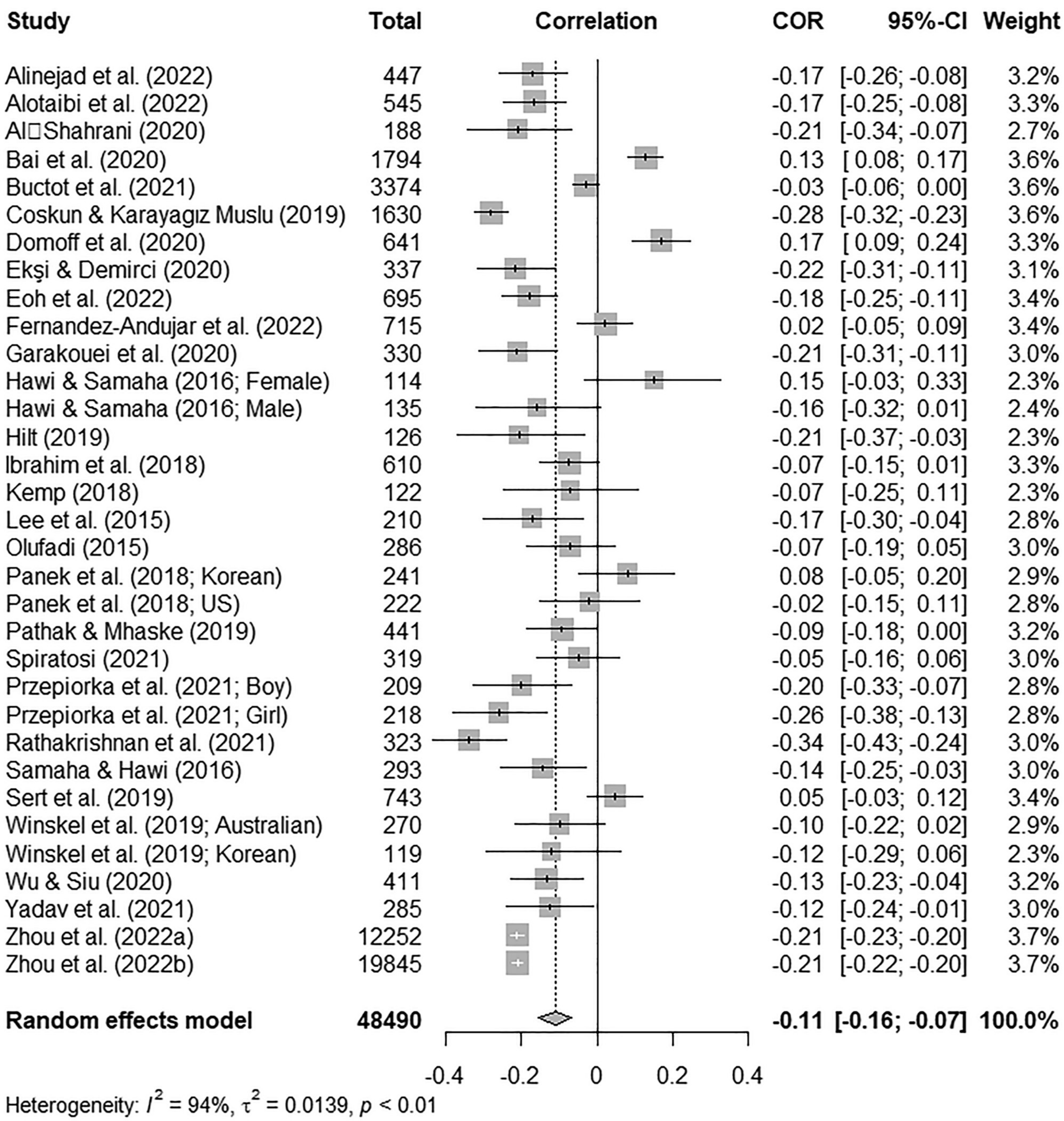

Fig. 2. Forest plot of the relationship between PSU and academic achievement

perceiving autonomy support from teachers (Okada, 2021). Second, that it appears to be weaker (and respectively of equal and opposite sign) than those reported for (i) experiences specific to teaching-learning processes such as feeling burnout (Madigan & Curran, 2021); and (ii) personality factors such as conscientiousness (i.e., to be self-disciplined and organized) (Mammadov, 2022), demographical variables such as family socioeconomic status (Liu et al., 2020), personal capabilities such as cognitive ability (Mammadov, 2022), or cognitions concerning academic self-efficacy (Honicke & Broadbent, 2016). Based on the aggregation of currently available data, the findings of the present study support the potentiality of considering PSU as one of the possible determinants of decreased academic achievement. Given the large number and varying nature of the factors suggested as likely determinants of academic performance (Nunes, Oliveira, Santini, Castelli, & Cruz-Jesus, 2022), further research is needed to clarify the specific or complementary explanatory role of PSU.

Moderators of the relationship between PSU and academic achievement

The fact that neither academic achievement indicator, publication status, year of publication, quality, nor the continuous or dichotomous nature of PSU assessment were

Table 2. Results of univariable meta-regression analysis

			95% CI			95% CI				
Moderators	*k*	β_0	Lower	Upper	β_1	Lower	Upper	Omnibus test	*p*	R^2
Sex	33							F (2, 30) = 0.569	0.572	0.00
Female (RC)	3	−0.112	−0.277	0.053						
Male	3	**−0.194**	**−0.358**	**−0.029**	−0.081	−0.314	0.152			
Both	27	**−0.104**	**−0.154**	**−0.054**	0.008	−0.164	0.181			
Educational level	33							F (3, 29) = 3.327	0.033	21.80
Tertiary [College] (RC)	18	**−0.092**	**−0.150**	**−0.034**						
High School	9	**−0.117**	**−0.195**	**0.040**	−0.025	−0.122	0.072			
Elementary/Middle School	5	**−0.214**	**−0.316**	**−0.113**	**−0.122**	**−0.239**	**−0.005**			
Elementary/Middle School and High School	1	0.129	−0.086	0.344	0.221	−0.002	0.444			
Academic achievement indicator	33							F (3, 30) = 1.24	0.179	6.90
GPA (RC)	24	**−0.116**	**−0.169**	**−0.063**						
Test scores	6	**−0.154**	**−0.254**	**−0.054**	−0.037	−0.151	0.076			
Self-reported grades	3	0.004	−0.135	0.143	0.120	−0.029	0.269			
PSU assessment	33							F (1, 31) = 0.109	0.744	0.00
Continuous (RC)	27	**−0.108**	**−0.159**	**−0.058**						
Categorical	6	**−0.128**	**−0.240**	**−0.016**	−0.020	−0.143	0.103			
Region	33							F (2, 30) = 0.922	0.409	0.93
Non-Western (RC)	24	**−0.197**	**−0.181**	**−0.074**						
Western	8	**−0.057**	**−0.151**	**0.038**	0.071	−0.038	0.179			
Unknown	1	**−0.144**	**−0.408**	**0.120**	−0.017	−0.286	0.253			
Publication status	33							F (1, 31) = 0.300	0.588	0.00
Published (RC)	31	**−0.114**	**−0.162**	**−0.067**						
Unpublished	2	−0.060	−0.258	0.139	0.055	−0.149	0.259			
Continuous moderators										
Age	20	**−0.219**	**−0.419**	**−0.020**	0.007	−0.004	0.018	F (1, 18) = 1.672	0.212	3.42
Percentage of females	32	**−0.193**	**−0.311**	**−0.076**	0.146	−0.054	0.346	F (1, 30) = 2.226	0.146	3.86
Year of publication	33	**−0.168**	**−0.255**	**−0.081**	0.016	−0.005	0.038	F (1, 31) = 2.354	0.135	3.78
Quality	33	−0.063	−0.410	0.284	−0.005	−0.044	0.033	F (1, 31) = 0.084	0.774	0.00

Note. β_0 = Intercept/mean effect size; β_1 = Estimated regression coefficient; R^2 = Explained variance; RC = Reference category; GPA = Grade Point Average; PSU = Problematic smartphone use. Statistically-significant effects ($p < 0.05$) appear highlighted in bold.

found to significantly moderate the relationship between PSU and academic achievement suggests that its size tends to be largely unaffected by methodological issues. Regarding socio-demographic variables, the fact that neither sex, region, nor age emerged as significant moderators of the relationship under consideration suggest it to be largely consistent in size across individuals with different socio-demographic characteristics. These results are noteworthy if it is assumed that PSU has a potential influencing effect on academic achievement (Baert et al., 2020; Dontre, 2021).

Concretely, the results presented here provide preliminary support for the implementation of actions focused at dealing with PSU as a largely universal effective strategy towards fostering academic achievement. It is also conceivable that such actions could be particularly effective in the case of primary and secondary school students. This is at least what would be expected from the results of the moderation analyses which show larger sizes of the relationship under consideration in the samples corresponding to these population groups. This latter finding also suggests that younger individuals may be more vulnerable to the potential negative consequences of PSU. This possibility seems plausible given the evidence linking the initiation of smartphone use during elementary education with subsequent increases in PSU, as well as reductions in both self-directed learning ability and academic achievement (Han, 2022).

Practical implications

Findings from the present study suggest the need to raise awareness of the potentially detrimental effects of the PSU in terms of its potential negative impact on successful academic achievement. This would make it advisable to increase efforts targeted at achieving two different objectives. Firstly, to identify students who, at least partially because of presenting high PSU levels, may be at risk of underachievement and school failure. This could be done, for example, by employing psychometric screening tests that could be applied to both students and external informants such as parents (Eoh, Lee, & Park, 2022). Secondly, to design, implement, and test the effectiveness of educational and dissemination initiatives aimed at improving academic achievement by preventing the occurrence of PSU. These initiatives could focus on instructing students in the adoption of strategies that have proven useful in reducing PSU, including but not limited to (i) replacing part of the time spent on smartphone use with potentially pleasurable and health-promoting activities such as informal physical activity or sports (Precht et al., 2024); or (ii) adopting responsible patterns of use such as disabling non-essential notifications, keeping the smartphone in silent mode when not in use throughout the day or when going to bed, or leaving it at home when it is not needed (Olson et al., 2022). These initiatives could also be extended to parents -particularly those of younger students - who could be instructed on how to implement effective supervisory/technical and restrictive mediation of children's and adolescents' smartphone use (Chang et al., 2019).

Limitations

It is pertinent to highlight the limitations of the present study for the purpose of properly interpreting the findings presented and to provide promising avenues for future research. First, all available data were cross-sectional, which prevents drawing conclusions regarding causality based solely on findings from the present study. Future research using longitudinal designs is therefore needed to corroborate the theoretical plausibility of considering PSU as an antecedent of academic achievement (Baert et al., 2020; Dontre, 2021).

Second, aggregated scores rather than scores on the different factors included in the instruments assessing PSU were mainly available, which prevented the quantification of the precise relationship between each of them and academic achievement. This limitation is important considering (i) the multidimensional nature of many of the psychometric instruments used to assess PSU (Harris et al., 2020); and (ii) that there is evidence suggesting that the strength of the relationship between PSU and some of its potential consequences may vary across specific dimensions of the former (Gugushvili et al., 2020; Olufadi, 2015). In the absence of consensus on the definition and self-reported measurement of PSU, further research in this area is needed that approaches PSU not just as a unidimensional construct but also in terms of the range of possible dimensions involved in such a phenomenon.

Third, the evidence concerning PSU consisted exclusively of self-reported data that was not accompanied by objective smartphone usage data (Ryding & Kuss, 2020). This is an important limitation given the weak association between objective (account-based) and subjective (self-reported) smartphone use data (Parry et al., 2021). This also implies that the potentially differential and/or complementary role of problematic and required or non-necessarily problematic use in explaining academic achievement (Buctot, Kim, & Kim, 2021; Ryding & Kuss, 2020; Troll, Friese, & Loschelder, 2021) could not be elucidated. On the other hand, the fact that self-reported data concerning academic achievement were based on objective evidence (e.g., the objective collective collection of GPA data) (Sapci, Elhai, Amialchuk, & Montag, 2021) was not entirely clear in all the retrieved studies that presented self-reported grades. In view of these two limitations, future studies should consider accompanying self-reported data concerning both GPA and PSU with those that, ideally derived from passive objective measures, allow for obtaining (i) evidence-based GPA data and (ii) automated, continuous, and unobtrusive collection of smartphone usage patterns data (e.g., in terms of time, length of specific apps use, or number of received or attended notifications) (Ryding & Kuss, 2020).

A final limitation to note is that data gathered refer exclusively to general smartphone use. This limitation is relevant in the light of evidence suggesting that further consideration of specific PSU (i.e., accessing specific applications such as social media platforms) may lead to a more comprehensive explanation of the possible real-life consequences of this phenomenon (Chen et al., 2020; Elhai et al., 2021; Rozgonjuk, Sindermann, Elhai, & Montag, 2020). This limitation calls for future research that provides deeper insight into the differential or complementary impact of general and specific types of PSU on academic achievement.

CONCLUSIONS

In summary, the findings of the present meta-analysis contribute to the understanding of one of the factors potentially implicated in decreased academic achievement by providing evidence that points to PSU being one of them. It is therefore conceivable that implementing actions aimed at decreasing students' PSU (particularly at the elementary and middle school level) may translate into improved academic achievement. The fact that all available evidence on the topic under investigation comes from cross-sectional studies points to the need for longitudinal research aimed at clarifying the direction of the likely temporal relationship between PSU and academic performance. These research efforts may benefit from (i) considering the range of specific components involved in PSU; (ii) implementing differentiated assessment of PSU of a general nature (i.e., that focused on the device itself) and of a specific nature (i.e., that focused on the type of content and/or applications accessed through the device); and (iii) complementing data derived from self-reported psychometric scales and questionnaires with objective data. Such research would likely shed light on the particular circumstances under which students' PSU may negatively affect their academic achievement.

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drafting of the manuscript and revisions. All authors assisted with drafting of the final version of the manuscript, including critical revisions for intellectual content.

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SUPPLEMENTARY MATERIALS

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