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Boredom and digital media use: A systematic review and meta-analysis

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ABSTRACT

Nowadays, digital media, especially smartphones, allow to alleviate boredom quickly and conveniently. Numerous studies investigated the relationship between boredom and digital media use, including problematic use. However, a comprehensive overview of these studies is still missing. Following a systematic database search and screening process, we identified 59 empirical studies on boredom and (problematic) digital media use published since 2003. Most studies were cross-sectional (n=52) and focused on problematic use (n=32). The meta-analysis showed a medium-to-large positive association (r=.342) between boredom and problematic digital media use, whereas a small-to-medium association (r=.084) was found for boredom and digital media use. Subgroup analyses showed no differences with respect to sample characteristics, study design, boredom measures, and type of digital media use. However, studies investigating general Internet use reported a stronger association with boredom. Future research should use longitudinal designs to disentangle the direction of the association between boredom and (problematic) digital media use.

1. Introduction

"The 'age of boredom' [...] has now passed. The principal culprits are thought to be the culture industries, and, more recently, the internet, together with the digital technologies that allow us to access it. Under such conditions, it seems that the time needed to be bored is no longer available." (Holmboe & Morris, 2021, p. 2). This statement stands in contrast to the continued scientific interest in the concept of boredom, especially in the context of digital media use. In fact, although there are seemingly unlimited possibilities at a fingertip, boredom is still a prevalent phenomenon today. By summarizing different conceptualizations, Tam et al. (2021) described boredom as an unpleasant experience in which people perceive time as passing slowly; they feel restless, trapped, unchallenged, and perceive the situation, and perhaps life, as meaningless.

Prevalence rates of boredom vary, for example, depending on the population's age. A study with 21'173 adolescents taking part in the Monitoring the Future survey in the US identified that approximately 20 percent reported high levels of boredom (Martz et al., 2018). Based on the same survey, another study using data from 106'784 adolescents showed an increasing trend in boredom since 2008, especially among girls (Weybright et al., 2020). In an experience sampling study with data from 3'867 adults in the US, the authors found that 63 percent reported having been bored at least once over the 10-day assessment period (Chin et al., 2017).

Additionally, the difference in prevalence rates also depends on the conceptualization and, consequentially, the assessment of boredom. In particular, boredom can be either a temporary mood state caused by insufficient contextual stimuli (i.e., situation-induced or acute boredom) or a personal, trait-like characteristic describing the tendency of experiencing boredom in a wide range of situations (i.e., person-specific or chronic boredom). State boredom is closely linked to the notion that boredom results from an interaction between the situation and the person (Mercer-Lynn et al., 2014). Trait boredom, on the other hand, has been recently considered as a chronic lack of agency, which "makes it difficult to realize intentions, to execute, and persist with activities to achieve desired goals [which] thus results in the frequent experience of boredom" (Gorelik & Eastwood, 2023, p. 4). To overcome a mere state-trait dichotomy, Fahlman et al. (2013) proposed a transtheoretical definition of boredom characterized by (a) lack of engagement in satisfying activities, (b) low arousal negative affect due to situations being perceived as redundant, monotonous, or meaningless, (c) high arousal negative affect resulting from restlessness, agitation, and frustrating of being bored, (d) the experience of time dragging on, and (e) having difficulties focusing attention.

In their review of self-report boredom measures, Vodanovich and

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Watt (2016) further distinguish between general and context-specific boredom, where the latter refers to state or trait boredom experienced in distinct contexts such the academic context, work, leisure time, or relationships. Although one might object that trait boredom is context-specific – given its definition of being a personal, stable characteristic – the distinction should be seen in response to the measures that have been developed and applied to date. Context-unspecific state or trait boredom measures include, among others, the 29-item Multidimensional State Boredom Scale (MSBS) (Fahlman et al., 2013) and its 8-item short version proposed by Hunter et al. (2016), the general 28-item Boredom Proneness Scale (BPS) (Farmer & Sundberg, 1986) and its short versions (BPS-SF-8 by Struk et al., 2015; BPS-SF-12 by Vodanovich et al., 2005), or the 10-item Boredom Susceptibility subscale of the Sensation-Seeking Scale (ZBS) (Zuckerman et al., 1978). In contrast, context-specific state boredom measures refer to, for example, the work (e.g., Dutch Boredom Scale (DUBS); Reijseger et al., 2013) and academic context (e.g., Achievement Emotions Questionnaire (AEQ); Pekrun et al., 2014). Furthermore, context-specific trait boredom measures include the 16-item Leisure Boredom Scale (LBS) (Iso-Ahola & Weissinger, 1990), the 6-item boredom subscale of the Leisure Experience Battery (LEB) (Caldwell et al., 1992), and the Sexual Boredom Scale (SBS) (Watt & Ewing, 1996).

Whether context-specific or not, whether a state or a trait, boredom has been associated with various risks and adverse behaviors. These include, among others, substance use and delinquency (Wegner & Flisher, 2009), emotional eating (Koball et al., 2012), risky driving (Dahlen et al., 2005), and risky gambling (Kılıç et al., 2020; Mercer & Eastwood, 2010). In the context of digital media use, boredom has been associated with hypersexuality (De Oliveira & Carvalho, 2020), cyberbullying (Graf et al., 2019; Zhang et al., 2022), exposure to antisocial media content (Zhang et al., 2022), and cyberloafing, which is the use of the Internet in inappropriate contexts, e.g., Internet use at work for private purposes (Pindek et al., 2018).

Yet, digital media use is nuanced, thus posing the question of the role of boredom across different digital devices, including stationary (e.g., smart TV, PC) and mobile media (e.g., smartphone, tablet), as well as different activities. For example, smartphone penetration reached 78 percent worldwide, with higher percentages among younger populations and in developed countries (O'Dea, 2021), providing easy access to social media platforms, such as Facebook, Instagram, TikTok, LinkedIn, or Snapchat, which are used by 4.6 billion people worldwide (Dixon, 2022).

Also, during the last decade, a major concern arose regarding the problematic use of digital media, including the problematic use of social media, smartphones, and the Internet in general (World Health Organization, 2015, pp. 27–29). Problematic digital media use shares similar characteristics with substance-related addictions (Marciano et al., 2021; Rosenberg & Feder, 2014): (a) excessive use (i.e., usage longer than intended), (b) salience (i.e., constantly thinking about using digital media), (c) mood modifications (i.e., being in a good mood when using digital media and in a bad mood when not), (d), tolerance (i.e., urge to use digital media more to obtain the same gratifications), (e) withdrawal symptoms (i.e., anger, restlessness, or anxiety when not using digital media), (f) relapse (i.e., unsuccessful attempts to reduce digital media use), and (g) conflict (i.e., neglect of other activities and conflict in interpersonal relationships resulting from excessive digital media use) (Billieux et al., 2015; Kuss & Griffiths, 2017; Young, 2004). Problematic digital media use has been associated with different psychosocial problems such as anxiety, depression, stress, sleep problems, sedentary behaviors, and loneliness (Al-Samarraie et al., 2021; Ratan et al., 2021; Sohn et al., 2019). Nevertheless, to date, Internet Gaming Disorder is the only digital media-related behavioral addiction included in the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) as a condition warranting more clinical research (American Psychiatric Association, 2013). Consequently, to avoid the notion of a not (yet) established pathology, many researchers have opted for the term 'problematic use' when referring to digital media-related addictions, including problematic smartphone, Internet, and social media use. We do so too in the present review.

To sum up, research on the relationship between boredom and problematic digital media use is growing, and it is now time to systematically summarize and critically discuss the existing evidence on the relationship between (trait and state, context-specific and context-unspecific) boredom and (problematic) digital media use. Before we describe the applied methodology and summarize our results, we provide a brief overview of selected theoretical frameworks behind the possible associations between boredom and (problematic) digital media use.

1.1. Theoretical background

The scientific literature on boredom proposes different theoretical frameworks for its causes and consequences. We focus on two recent and comprehensive theories, which follow up on well-established theories in psychology and communication sciences: the Meaning-and-Attentional-Components (MAC) model (Westgate, 2020; Westgate & Wilson, 2018) and the Boredom Feedback Model (BFM) (Tam et al., 2021). In addition, we briefly summarize the Interaction of Person-Affect-Cognition-Execution (I-PACE) model for addictive behaviors (Brand et al., 2019) and the model of Compensatory Internet Use (CIUT) (Kardefelt-Winther, 2014) to explain the theoretical link between boredom and problematic digital media use.

The Meaning-and-Attentional-Components (MAC) model (Westgate, 2020; Westgate & Wilson, 2018) posits that boredom results from an interaction between attention to (or cognitive effort needed for) a specific activity, which can result either from under stimulation (i.e., too unexciting, too easy) or overstimulation (i.e., too demanding, too difficult), and from the meaning (or personal relevance) attached to the activity (i.e., high vs low meaning). For example, people feel bored when they engage in meaningless activities despite attention variations ranging from under-to overstimulation. But they also experience boredom during high-meaning activities if under- or overstimulated. Whereas, when meaning and the right amount of attention or cognitive effort match, people are not bored (Leung, 2020), and they may potentially enter a flow state characterized by deep and effortless concentration (Marty-Dugas & Smilek, 2019). According to the definition of flow, people enjoy an activity the most when the challenge of the activity matches their skills. Too much challenge brings frustration, while the opposite brings boredom (Csikszentmihalyi, 1990). Poels et al. (2022) applied the MAC model to describe different scenarios where boredom determines subsequent mobile media use, for example, in the form of sensation-seeking to escape a low-meaning and under-stimulated situation, or in the form of hedonic media use such as distraction and relaxation to cope with a low-meaning and overstimulated situation. Furthermore, according to the authors, boredom can lead to phubbing or (media) multitasking when under-stimulated as they have additional cognitive resources to engage in more than one (media) activity.

The Boredom Feedback Model (BMF) (Tam et al., 2021) is another recently developed model explaining different mechanisms to cope with boredom. When bored, people "may shift out to external things that are unrelated to the source of boredom (i.e., the boring situation or the stimulus), shift inward (e.g., mind-wandering, self-reflection), or shift back to the source of boredom." (p. 259). People may shift out towards highly gratifying digital media contents as a form of escapism, as previously described in the MAC model. The BMF considers 'shifting out' an avoidance strategy, where the source of boredom is not sufficiently appraised and self-control processes are activated. Furthermore, the repeated avoidance of boredom through digital media use may turn into triggered digital media use as a form of anticipating the slightest feeling of boredom.

This trigger mechanism is closely related to assumptions from the

Person-Affect-Cognition-Execution (I-PACE) model for addictive behaviors (Brand et al., 2019) and the model of Compensatory Internet Use (CIUT). These models state that if people learn through repetition that digital media use (e.g., online gaming, smartphone use) is effective in alleviating negative feelings such as boredom, they rely on this coping strategy in future boring situations to the extent that they become dependent on this compensatory form of digital media use, resulting in problematic (or addictive) forms of usage. According to the I-PACE model (Brand et al., 2016, 2019), compensatory digital media use outweighs gratifying digital media use in the later stages of addiction, when people's inhibitory control is further reduced due to feelings of graving for digital media use as a response to boring situations. In sum, from a theoretical perspective, boredom is considered a precursor of (problematic) digital media use, though one should keep in mind that digital media use may as well be experienced as 'boring' when it is not sufficiently meaningful and/or arousing.

1.2. Study aim

To date, different reviews exist on the concept of boredom focusing, among others, on physiological correlates (Raffaelli et al., 2018), measurement (Vodanovich & Watt, 2016), specific populations (Marshall, McIntosh, et al., 2020; Marshall, Roy, et al., 2020), and settings (e.g., De Oliveira & Carvalho, 2020; Tze et al., 2016; Wegner & Flisher, 2009). Boredom has been furthermore discussed in the context of (digital) media use (Poels et al., 2022; Vedechkina & Borgonovi, 2021), but a holistic approach is missing. In the present systematic review and meta-analysis, we aim to collect scientific evidence on the relationship between boredom and digital media use by differentiating between different forms of boredom (i.e., general trait vs context-specific trait vs state boredom) and digital media use (i.e., problematic vs non-problematic digital media use). Furthermore, we aim to explore whether the relationship between the two differs for types of digital media use (e.g., smartphone use, social media use, gaming), socio-demographic characteristics (e.g., gender, age), and study characteristics (e.g., cross-sectional vs longitudinal, continent of data collection).

2. Methods

We conducted the preregistered systematic review (PROSPERO 2022 CRD42022304721) following the updated Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) statement (Page et al., 2021). We complemented the qualitative synthesis of the findings with a meta-analysis on a subset of studies with comparable effect sizes.

2.1. Search strategy and study selection

On January 14, 2022, we systematically searched in the following ten academic databases: Communication and Mass Media Complete, Psychology and Behavioral Sciences Collection, and PsycINFO (all via EBSCOhost), ERIC (Educational Resource Information Center), Sociological Abstracts, and Sociology Database (all via ProQuest), Medline (via ProQuest, Web of Science, and PubMed), Web of Science, PubMed, and Scopus. Following the PICO (Population, Intervention, Comparison, Outcome) framework, our search strategy included keywords capturing the concepts of boredom (i.e., bored*) and digital media use (e.g., smartphone, social media, social network*, screen time, digital, online, Internet). Given our interest in all age groups, we did not define a specific population. Furthermore, since we were interested in observational studies looking at the relationship between boredom and digital media use, we did not define a comparison group in the PICO criteria, as it is the case in randomized controlled trials in clinical research. We combined our keywords with the Boolean AND- and OR-operators to search in title and/or abstract. For more details on the search strategy, see Supplement 1, Table 1. To ensure that we did not miss recent publications, we conducted an additional hand search on June 14, 2022, by screening the first 100 entries in GoogleScholar for "boredom digital media", "boredom smartphone", and "boredom social media", respectively. To restrict the search results, we applied a filter to articles published since 2021.

We imported all extracted publications into Zotero to remove any duplicates. After duplicate removal, the first two authors independently screened the identified titles and abstracts for eligibility. Next, the first author performed the full-text screening of all retained articles, with the decisions checked by the second author. At each step, discrepancies were resolved through discussion among all authors until consensus was achieved.

2.2. Inclusion and exclusion criteria

During title and abstract screening, publications were included if they (1) were published in English in a peer-reviewed journal, (2) included an original empirical study, (3) investigated the relationship between boredom and (problematic) digital media use, and (4) included participants from the general population. We excluded (1) publications not published in English, (2) qualitative research papers, reviews, meta-analyses, case studies, comments, books, book chapters, theses, reports, and conference proceedings, (3) studies including clinical populations, (4) studies focusing on (online) sexual behavior, (online) learning environments (including distant learning), (online) shopping behavior, or offline gaming/gambling, (5) studies that did not use a unique empirical measure of boredom (e.g., boredom in combination with other negative affect measures), (6) studies that did not use a unique empirical measure of (problematic) digital media use (e.g., online and offline gaming combined), and, finally, (7) studies that did not assess the relationship between boredom and (problematic) digital media use.

2.3. Data extraction and meta-analytic procedure

From each retained publication, we extracted information on the study characteristics, including the country where the study was conducted, study design (correlational vs longitudinal), type of data collection (online vs offline), sampling procedure (convenient vs probabilistic), information on the analytical sample (sample size, % of males, age), and context (Covid-19). We further extracted information on the theoretical framework(s) of the study, the concepts of boredom (trait or state) and digital media use (problematic vs non-problematic), and the measurement of each concept. We eventually took note of the applied statistical analysis and the main result.

For the meta-analysis, we extracted the following effect sizes: Pearson's r, Spearman's *rho*, as well as regression coefficients and ANOVA test statistics when correlation coefficients were not available. We kept effect sizes for trait and state boredom as well as digital media use and problematic media use separate but aggregated across different types of digital media use and samples, when more were used in a study. We carried out the meta-analysis using the "meta" package (Balduzzi et al., 2019) in R statistical software. We used Fisher's r-to-z transformation as a measure of effect size, with results converted back to r correlation coefficient for easier interpretation. Given that the raw data were heterogeneous, we used different conversion formulas (Bonett, 2007; Peterson & Brown, 2005; Wan et al., 2014). We used the "esc" package (Lüdecke, 2019) to calculate the final effect size. We pooled the effect sizes for the relationship between boredom and digital media use in general, and boredom and problematic digital media use. We interpreted the pooled effect sizes according to recommendations by Funder and Ozer (2019) for psychological research: Effect sizes of 0.05, 0.10, 0.20., 0.30, and <0.40 were interpreted as "very small", "small", "medium", "large", and "very large", respectively. To control for studies' diversities, each meta-analysis was run using the inverse-variance method with a random effects model and Hartung-Knapp-Sidik-Jonkman adjustment (IntHout et al., 2014). We calculated the heterogeneity of the effect sizes with the between-study-variance τ2, using the restricted maximum-likelihood estimator (REML) (Borenstein et al., 2010; Higgins et al., 2003; Ried, 2006). The inconsistency (I^2) statistic was used to reflect the size of the heterogeneity, and it was interpreted as low (25%), moderate (50%), and high (75%), according to Higgins et al. (2003). Potential publication biases were explored graphically *via* funnel plots and statistically with Egger's regression tests for funnel plot asymmetry (Egger et al., 1997). Furthermore, to explore heterogeneity in the effect sizes, we carried out influence analyses (using the leaving-one-out method), sub-group analyses, and meta-regressions. Sub-group analyses were run to differentiate the effects of different moderators, such as the way in which boredom was conceptualized (i.e., general trait vs context-specific trait vs state) and the type of digital media use investigated (i.e., social media, smartphone, Internet, gaming, or digital technology in general). We also considered different socio-demographic (i.e., age categories) and study-specific characteristics (i.e., study design, continent of data collection) as moderators. Meta-regressions were used to investigate the influence of gender (i.e., % of male participants).

2.4. Methodological quality assessment

We assessed the quality of each retained article by applying a modified version of the Quality Assessment Tool for Observational Cohort and Cross-sectional Studies developed by the NIH (NHLBI, 2021). Our modified tool comprises a 10-item checklist evaluating each study regarding potential selection bias introduced by sampling choices (e.g., convenience vs probabilistic), measurement bias introduced by choice of scales to measure boredom and digital media use (e.g., validated, multi-item vs ad-hoc measures), confounding introduced by the authors' choices concerning the handling of missing values and statistically adjusting for covariates in the final models, as well as the a-priori

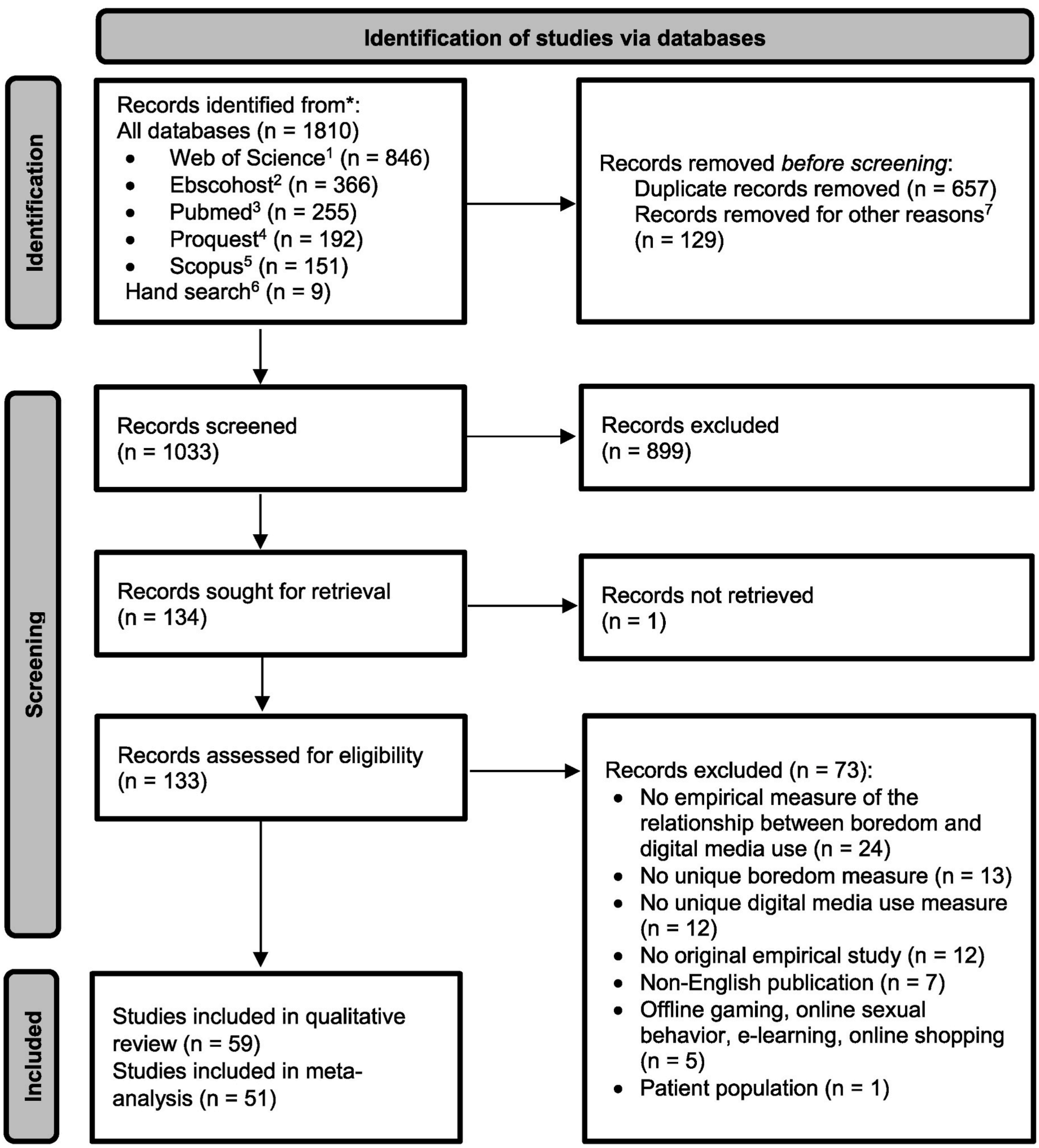

Fig. 1. PRISMA flowchart.

statement of research questions and/or study hypotheses and the appropriateness of the study design to answer/test them (e.g., cross-sectional vs longitudinal). For each item, we evaluated if the quality criterion was met (1) or not (0) or whether the information was missing so that the quality could not be determined (0). A sum score was created with a higher score indicating better methodological quality. Following an initial training phase on a common subset of seven studies, the first and second author each evaluated half of the remaining studies independently.

3. Results

The systematic database search resulted in 1810 records, complemented by nine records identified through the hand search. After duplicates (n = 657) and non-peer-reviewed articles (n = 129) were removed, we screened the titles and abstracts of 1033 records for eligibility, resulting in the exclusion of 899 records. Inter-coder reliability for the title and abstract screening was good (Cohen's kappa = .797). Because one record could not be retrieved, we performed the full-text screening on 133 records. Of these, we excluded 73 records because they did not include empirical measures of the relationship between boredom and digital media use (n = 24), did not use a measure of boredom (n = 13) or digital media use (n = 12), were not an original empirical study (n = 12), were not published in English (n = 7), measured offline gaming, online sexual behavior, e-learning, or online shopping (n = 5), or included a clinical population (n = 1). This stepwise screening process resulted in 59 articles included in the qualitative synthesis and 51 studies included in the meta-analysis, of which one study provided two effect sizes for boredom and digital media and (Biolcati et al., 2018) and one study provided two effect sizes for boredom and problematic digital media use (Donati et al., 2022). The updated PRISMA flowchart in Fig. 1 summarizes the study selection process.

3.1. Study characteristics

The 59 included studies were published between 2003 and 2022. Thirty-seven studies (63%) were published after 2019, of which eight considered the context of the Covid-19 pandemic. The 59 studies report findings from 61 study samples. Twenty-seven samples were recruited in Asia (China, Taiwan, and Indonesia), ten in North America (US), ten in Europe, six in the Middle East (including Turkey and Gulf region), and two in Oceania (Australia). Two studies (Al-Saggaf, 2021; Lin et al., 2020) collected data from multiple countries and two (Leung, 2020; Poon & Leung, 2011) did not specify the country. Most of the studies (n = 52) used a cross-sectional design; four were longitudinal, and three included Ecological Momentary Assessments (EMAs). Twenty-nine studies reported on collecting data online, ten offline (e.g., through paper-and-pencil questionnaires at school and in other unspecified contexts), and three through Computer-Aided Telephone Interviewing (CATI) and in-app questionnaires. Seven studies did not specify the method of data collection. The analytical sample size ranged from 83 (Dora et al., 2021; Lekkas et al., 2022) to 21'173 participants (Martz et al., 2018); with a median of 440 participants.

Most of the study samples (n = 42) were fairly balanced in gender distribution, with the proportion of males ranging from 33 to 65 percent. Thirty-two studies collected data from young adults, 29 of them including university students, 12 studies collected data from adults, nine from adolescents, and six from a mix of different age ranges. Supplement 1, Table 2 includes a summary of the study characteristics, while Supplement 1, Table 3 presents the characteristics of each study included.

3.1.1. Boredom measures

To group and describe the boredom measures used in the included studies, we referred to the literature review by Vodanovich and Watt (2016), who differentiate between state and trait boredom measures, with a further specification of context-unspecific and context-specific measures briefly summarized in the introduction of this paper. Based on their classification, 28 out of 59 studies (47%) considered boredom as a general (context-unspecific) trait, and the majority (n = 25) used the Boredom Proneness Scale (Farmer & Sundberg, 1986) both in its original and shortened versions. Nineteen studies (32%) measured context-specific trait boredom by focusing on the chronic experience of boredom during leisure time. Fifteen of them used different versions of the Leisure Boredom Scale (Iso-Ahola & Weissinger, 1990). Seven studies (12%) measured general state boredom, with Multidimensional State Boredom Scale (Fahlman et al., 2013) or ad hoc measures, and three studies measured context-specific state boredom, for example, at home during the Covid-19 lockdown (Yang et al., 2021). Donati et al. (2022) measured both state and trait boredom to compare their relationship with problematic Facebook use, while Kara (2019) measured both general and context-specific trait boredom in relation to problematic internet use.

3.1.2. Digital media use measures

Seventeen studies measured digital media use in terms of duration of use, frequency of use, or – more general – whether certain applications or contents are used at all. Studies focusing on the frequency of use asked participants to report on how often they used digital media (e.g., social media platforms) or engaged in specific activities (e.g., information-, social, or utility-oriented use). Likewise, studies focusing on the duration of use measured the daily time spent on digital devices in general or for specific activities such as browsing, posting, or sharing on social media. Two EMAs studies collected digital trace data on smartphone app use (Dora et al., 2021; Lekkas et al., 2022), and one EMAs study by Johannes et al. (2021) included trace data and in-app self-reports of social media use on the smartphone.

Ten studies included both a measure of digital media use and problematic digital media use, but the majority (n = 32) focused solely on problematic digital media use, with particular interest in problematic smartphone (n = 18), internet (n = 10), social media (n = 3), and online games use (n = 1). Problematic use was measured, among others, with (adapted versions of) the 17-item Mobile Phone Addiction Index (MPAI; Leung, 2008), the 10-item Smartphone Addiction Scale (SAS-SV; Kwon et al., 2013), and the 8-item Internet Addiction Test (IAT; Young, 1998).

3.2. Main results

The main results of this systematic review and meta-analysis are grouped into the relationship between (i) boredom and digital media use and (ii) boredom and problematic digital media use. Of the 59 included studies, 51 studies provided at least one effect size and were thus considered in different meta-analyses. The main meta-analytic results are shown here afterward, whereas funnel plots, sensitivity analyses, and additional subgroup analyses are reported in Supplement 2.

3.2.1. Boredom and digital media use

Twenty-seven studies investigated the relationship between boredom and digital media use. Of these, 21 effect sizes were considered in the meta-analysis, which showed a significant positive very small-to-small effect, meaning that boredom is related to higher use of digital media ($k = 21$, $r = 0.084$, 95% CI [0.039; 0.128], $p < .001$, $I^2 = 82\%$). The overall effect and levels of heterogeneity were not influenced by any specific studies. However, Egger's test for funnel plot asymmetry revealed the presence of publication biases ($t = 2.58$, $p = .0184$). Subgroup analyses showed no differences ($p = .268$) in effect sizes between measures, including boredom as a general trait ($k = 8$, $r = 0.067$, 95% CI [0.001; 0.132], $p = .047$, $I^2 = 75\%$) vs boredom as a context-specific trait ($k = 9$, $r = 0.070$, 95% CI [-0.020; 0.160], $p = .111$, $I^2 = 83\%$) vs boredom as a general state ($k = 4$, $r = 0.145$, 95% CI [0.010; 0.275], $p = .042$, $I^2 = 65\%$; Fig. 2). Further subgroup analyses results showed significant differences ($p = .002$) concerning the type of digital media use,

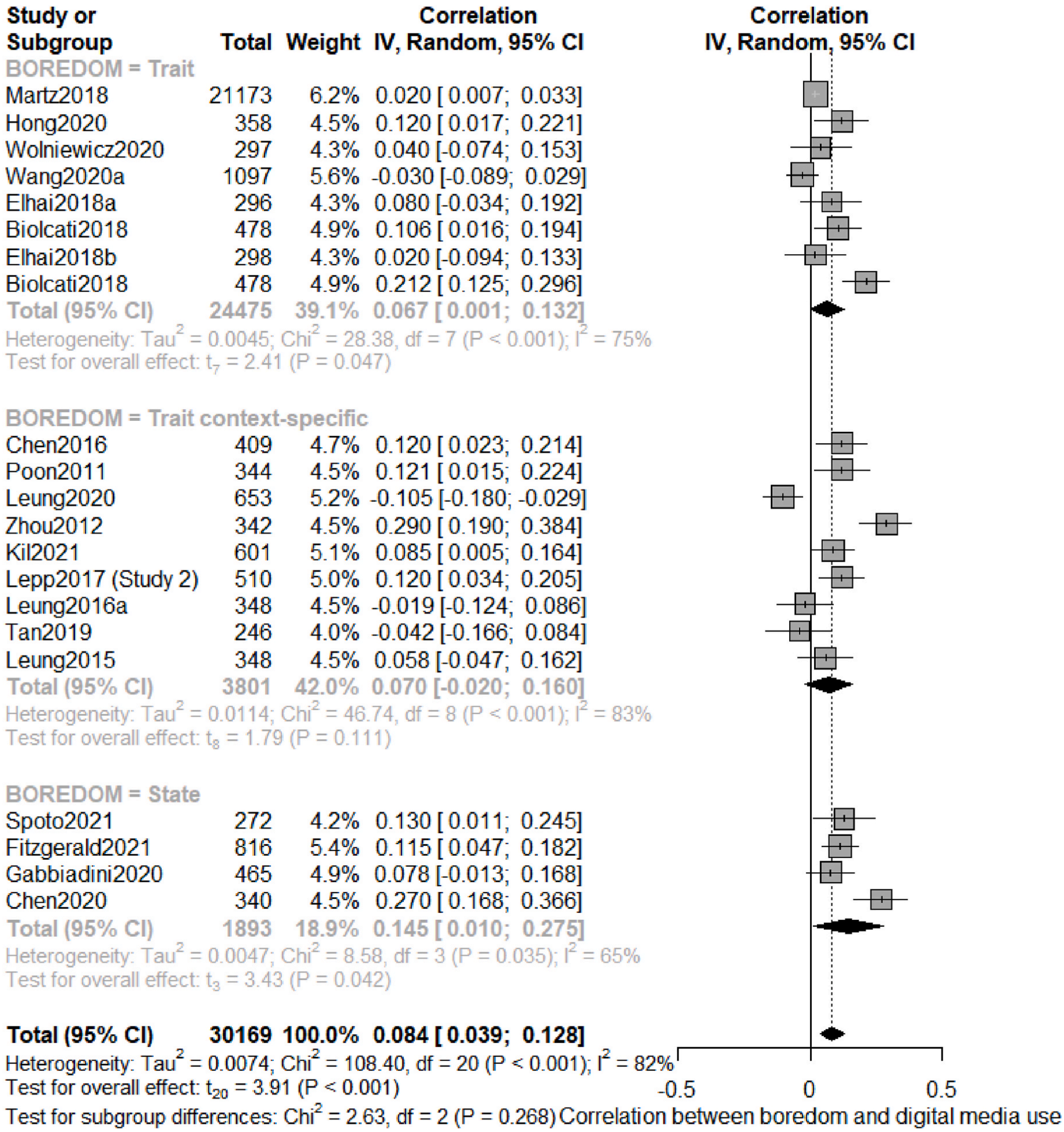

Fig. 2. Forest plot for state and trait boredom and digital media use.

with studies investigating general Internet use ($k = 4$, $r = 0.187$, 95% CI [0.074; 0.295], $p = .074$, $I^2 = 44\%$) reporting stronger associations with boredom (see also Table 1 and Supplement 2).

3.2.2. *Longitudinal and EMAs studies on boredom and digital media use*

One longitudinal study investigated the effect of boredom on thriving at home and career self-management during the Covid-19 pandemic, mediated by online leisure activities, e.g., finding challenging activities online and building relationships. Boredom was significantly associated with online leisure activities, but since both concepts were measured at T1, no causal relationships can be established (Chen, 2020). Two EMAs studies collected *in-situ* data on smartphone app use (Dora et al., 2021; Lekkas et al., 2022). Dora et al. (2021) collected data over three days from 83 PhD students in The Netherlands to analyze the reciprocal relationship between state boredom and smartphone use. The authors found that boredom increased the probability and subsequent duration of smartphone use and, *vice versa*, boredom levels were higher when the smartphone was used previously. In their study using EMAs data from the same sample of 83 PhD students collected over three days, Lekkas et al. (2022) found that overall duration of smartphone apps use and communication apps use were more influential in predicting subsequent levels of state boredom than proportional use of any single app type. Johannes et al. (2021) included both trace data and in-app self-reports of social media use on the smartphone collected from 96 university students in the UK over five days. They revealed that daily boredom was unrelated to subjective and objective daily social media use both at the within- and between-person level.

3.2.3. *Boredom and problematic digital media use*

Forty-two studies investigated the relationship between boredom and problematic digital media use. Of these, 40 effect sizes were considered in the meta-analysis, which showed a significant positive large-to-very large effect ($k = 40$, $r = 0.342$, 95% CI [0.287; 0.396], $p < .001$, $I^2 = 94\%$). Like in the context of digital media use, the overall effect and levels of heterogeneity were not influenced by any specific

Table 1
Summary of pooled effect sizes by subgroups.

	Digital media use	Problematic digital media use
Overall effect size (r)	.084*** (k = 21) [.039; .128]	.342*** (k = 40) [.287; .396]
Age		
Adolescents	.109* (k = 5) [.017; .200]	.277*** (k = 7) [.178; .371]
Adults, young adults	.075* (k = 16) [.018; .131]	.356*** (k = 33) [.291; .418]
Study design		
Cross-sectional	.072** (k = 19) [.028; .117]	.343*** (k = 37) [.282; .400]
Longitudinal	. 196 $^{n.s.}$ (k = 2) [-.661; .831]	.333* (k = 3) [.177; .473]
Continent of data collection		
North America	.177** (k = 7) [.023; .106]	.368*** (k = 6) [.282; .447]
Asia and Oceania	.097 $^{n.s.}$ (k = 8) [-.014; .205]	.354*** (k = 22) [.282; .423]
Europe	.132* (k = 4) [.035; .227]	.379** (k = 5) [.149; .570]
Other	.005 $^{n.s.}$ (k = 2) [-.893; .895]	.244 $^{n.s.}$ (k = 6) [-.074; .516]
Boredom		
General trait boredom	.067* (k = 8) [.001; .132]	.371*** (k = 26) [.307; .431]
Context-specific trait boredom	.070 $^{n.s.}$ (k = 9) [-.020; .160]	.268** (k = 11) [.121; .403]
State boredom	.145* (k = 4) [.010; .275]	.374* (k = 3) [.087; .603]
Type of digital media use		
Gaming	.177 $^{n.s.}$ (k = 3) [-.075; .408]	.289* (k = 4) [.090; .465]
Internet	.187** (k = 4) [.074; .295]	.308** (k = 10) [.124; .472]
Smartphone	.029 $^{n.s.}$ (k = 9) [-.032; .090]	.390*** (k = 21) [.332; .445]
Social media	.061 $^{n.s.}$ (k = 2) [-.493; .581]	.208 $^{n.s.}$ (k = 4) [-.154; .520]
Technology in general	.043 $^{n.s.}$ (k = 3) [-.083; .167]	.330 (k = 1) [.286; .373]

Note: $^{n.s.}$ $P > .05$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

study. Egger's test for funnel plot asymmetry was not significant, indicating the absence of publication biases (t = −0.28, p = .781).

Furthermore, subgroup analyses showed no differences (p = .308) in effect sizes between studies focusing on boredom as a general, context-unspecific trait (k = 26, r = 0.371, 95% CI [0.307; 0.431], p < .001, I^2 = 91%) vs boredom as a context-specific trait (k = 11, r = 0.268, 95% CI [0.121; 0.403], p = .002, I^2 = 97%) vs boredom as both a general and context-specific state (k = 3, r = 0.374, 95% CI [0.087; 0.603], p = .031, I^2 = 78%; Fig. 3). Also, effect sizes did not differ significantly with respect to participants' age, gender, continent of data collection, study design, or type of problematic digital media use (see also Table 1 and Supplement 2).

3.2.4. *Longitudinal studies on boredom and problematic digital media use*

Three out of four longitudinal studies examined the relationship between boredom and problematic digital media use, though the study by Yang et al. (2021) associated the two concepts at the same time point and thus cannot be considered a truly longitudinal study on the causal relationships between the boredom and problematic digital media use. Conducted during the Covid-19 pandemic, the authors found that boredom at T4 was positively associated with smartphone addiction at T4, controlling for quarantine, lockdown, loneliness, depression, all measured at T4, and previous levels of smartphone addiction measured at T3. Among the other two longitudinal studies, Hong et al. (2020) revealed that boredom partially and positively mediated the relationship between autonomy need satisfaction and problematic mobile phone use, each measured one year apart in a sample of 358 Chinese adolescents, while Zhang et al. (2021) found that boredom proneness positively predicted mobile phone addiction measured eight months apart and *vice versa*. There were no significant gender differences in the cross-lagged model applied to data from 352 Chinese university students.

3.3. *Quality of included studies*

The overall quality of the included studies varied considerably between 2 (Spoto et al., 2021) and 8 (Gabbiadini et al., 2020; Zhang et al., 2021) out of 10 possible scores. The average quality score across all studies was M = 5.4 (SD = 1.3, Md = 5.0). Most of the 59 included studies did not provide a justification for their sample size (n = 57), measured boredom and digital media use at the same time point, i.e., cross-sectional design (n = 53), relied on a convenience sample (n = 48), did not report on the participation rate of eligible persons and, if reported, had a participation rate of less than 50% (n = 37), and they did not report on missing data and how they were handled (n = 37). In addition, 23 out of 59 studies did not control for potential confounders, such as socio-demographic characteristics in main analysis. On the other hand, the great majority used validated measures of boredom (n = 55) and digital media use (n = 52). A detailed quality assessment of each study can be found in Supplement 1, Table 4.

4. Discussion

Nowadays, digital media, especially smartphones, allow to alleviate boredom quickly and conveniently to the point that some authors claim boredom may not exist anymore as people can rely on instantly gratifying contents and functionalities at any time and place (Holmboe & Morris, 2021). With the present review and meta-analysis, we summarized, for the first time, the empirical evidence on the relationship between boredom and digital media use, including problematic digital media use. Following a systematic database search and screening process, we identified 59 studies published between 2003 and 2022, of which eight focused on the context of the Covid-19 pandemic.

The first important finding is that most studies examined the relationship between problematic digital media use – including problematic internet use, smartphone use, social media use, and online gaming – and boredom. The pooled effect size was positive and large, while the pooled effect size across studies investigating the associations between boredom and digital media use was positive yet small. Thus, boredom is more strongly associated with problematic than non-problematic digital media use, providing evidence for the theoretical assumptions shared by the I-PACE model for addictive behaviors (Brand et al., 2019) and the CIUT model (Kardefelt-Winther, 2014). The models state that if people learn through repetition that digital media use (e.g., online gaming, smartphone use) is effective in alleviating boredom, they rely on this coping strategy in future boring situations to the extent that they become dependent on this compensatory form of digital media use. It is possible that as processes of acceleration and routinization associated with modern digital media intensify, the possibility of being constantly present online, tracking, and connecting are at once gratifying efforts to alleviate boredom (Hand, 2016). Furthermore, boredom may act as a "stop emotion" triggering disengagement from an ongoing task, thus promoting habit formation (Meijman, 1997). The repetition of such behavior would result in problematic use. This consideration aligns with a study that investigates boredom using EMAs and found that bored participants likely interacted more often with their smartphone afterwards (Dora et al., 2021). Similar findings exist for other negative emotional experiences associated with digital media use such as the fear of missing out (FoMO). For example, meta-analyses found more robust relationships between FoMO and problematic digital media use

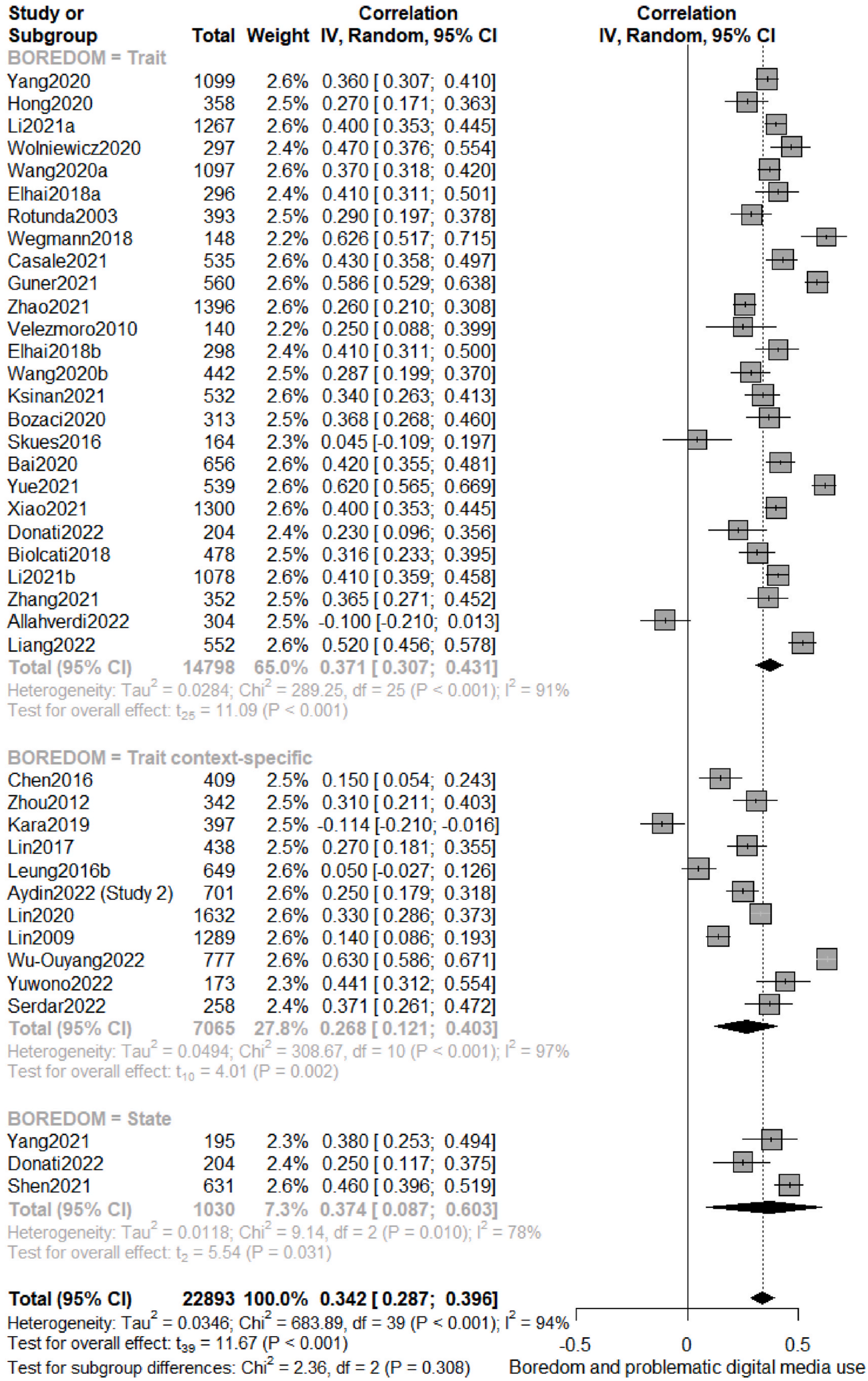

Fig. 3. Forest plot for state and trait boredom and problematic digital media use.

compared to FoMO and the non-problematic use of digital devices (Fioravanti et al., 2021; Yali et al., 2021). Thus, our results add to the identification of emotional experiences as risk factors associated with problematic digital media use.

The second important finding is that the relationship between boredom and (problematic) digital media use does not depend on moderating variables, including sample characteristics (e.g., gender, age, the continent of data collection), study design (e.g., cross-sectional vs longitudinal), and different types of digital media use (e.g., Internet, smartphone, social media, online gaming). The only exception concerns the relationship between boredom and general Internet use, for which we found a significantly stronger effect when compared to other activities such as smartphone and social media use or online gaming. However, since general Internet use encompasses many activities, it is hard to explain why the pooled effect size was larger. It is possible that, for example, when participants reported on general Internet use, they referred to on-demand activities such as online streaming and music listening (e.g., on YouTube, Netflix, Spotify), which may be consumed to alleviate boredom but can also be perceived as boring at some point. Further studies are needed looking into a wider range of online activities to shed light on boredom as a driver or consequence of Internet use.

The third finding worth discussing is that the significant positive relationship between boredom and (problematic) digital media use does not depend on the conceptualization of boredom as a temporal state vs a context-specific or unspecific trait. Based on this finding, we believe that measures of state boredom in observational studies outside a specific context – as the ones considered in the present review and meta-analysis – do not sufficiently capture the presence of a temporal state of under-stimulation or perceptions of doing a meaningless activity, as theorized in the MAC model (Westgate & Wilson, 2018). Scales of trait boredom, such as the frequently used Boredom Proneness Scale (Farmer & Sundberg, 1986) and the Boredom Proneness Scale-Short Form (Struk et al., 2015), require respondents to evaluate whether they feel bored "often", "in most situations", "much of the time". Similarly, studies measuring state boredom outside a specific context ask respondents to evaluate how often they feel bored or how strongly they agree to items measuring feelings of boredom without a specific context or activity in mind. Although evidence exists for the unique predictive power of state boredom over trait boredom, such evidence pertains to experimental settings where people find themselves in a concrete (manipulated) situation. In such situations, state boredom measures are advisable (Fahlman et al., 2013). In the present systematic review and meta-analysis of observational studies, only one (cross-sectional) study assessed state and trait boredom in the same sample (Donati et al., 2022). The authors found medium-to-large effect sizes between trait boredom and problematic Facebook use and between state boredom and problematic Facebook use. Although more studies comparing the two measures in relation to digital media use are needed, we recommend the use of state boredom measures only in experimental studies on digital media use as well as in studies using EMAs, which allow capturing how people feel "right now" and relating it to digital media activities they engage in just before, during, and just after.

Finally, the relationship between boredom and (problematic) digital media use was mainly studied cross-sectionally. Only three EMAs studies and two longitudinal studies measured boredom and (problematic) digital media use over time, indicating that boredom was a significant predictor of problematic usage behaviors, but also *vice versa*. This finding supports the I-PACE and CIUT model acknowledging that people may enter a vicious circle, i.e., boredom leads to problematic digital media use, which, in turn, results in higher levels of boredom as it becomes more and more difficult for people to satisfy their heightened needs for stimulation through digital media activities. Given the paucity of longitudinal evidence, we propose to conduct more longitudinal studies, especially EMAs studies, to understand better which digital media activities are perceived as boring. Also, according to the Boredom Feedback Model (BFM) (Tam et al., 2021), future research should investigate which online or offline contents cause or alleviate boredom, thus making people shift out to other external things or activities, shift inward, or shift back to the digital media activity. A more nuanced assessment of digital media activities using EMAs studies would further contribute to the ongoing debate on the (non-) sense of distinguishing between active and passive digital media use as can be witnessed in the context of social media use and well-being (Valkenburg et al., 2022). In general, theory-based hypotheses are needed to inform studies on specific digital media activities and boredom, and the MAC model and its distinction between arousal from and perceived meaningfulness of online activities is a good starting point (Poels et al., 2022). In particular, the MAC model helps categorizing online activities beyond the active-passive dichotomy since it considers the meaning and the stimulation conveyed by the activity. To this regard, it is also important to consider that boredom can give space for creativity and the creation of new ideas (Schubert, 1978) and foster problem-solving skills (Sio & Ormerod, 2009). To date, no study explored this link in the context of digital media usage. Additionally, more studies should focus on how boredom and digital media use change over the developmental years and according to different personality traits such as narcissism (Ksinan et al., 2021).

Another suggestion for future research concerns the selection of study samples. Most studies in this review collected data from Asian, European, and North American samples, and no study was conducted in South American and African countries. This is once again an example for the focus on Western, educated, industrialized, rich, and democratic (WEIRD) populations in research on digital media use, but future studies should include samples from all populations considering the steep update of and dependence on digital technologies in developing countries (Meng et al., 2022). Also, the overall quality of the studies included in this review was moderate. Little information was provided on the sampling strategy and possible biases due to non-response and missing values. Future studies should aim for representative samples, minimize non-response and report more information on how they handled missing values.

The present systematic review and meta-analysis has some limitations that should be acknowledged. For example, we did not include studies published in other languages than English, and we did not search for grey literature. In addition, we did not search for very specific types of digital activities that might have been studied in combination with boredom, such as aggressive online behaviors, the use of virtual reality, or e-learning. Future reviews should focus on specific online activities, which have unique characteristics and require different research questions to be synthesized.

5. Conclusion

The present systematic review and meta-analysis found that boredom is significantly and positively associated with digital media use and – to an even larger extent – problematic digital media use. Although the mostly cross-sectional studies do not allow conclusions on causality, theory helps explain these findings showing that digital media are used to alleviate feelings of boredom. At the same time, digital media activities themselves may be perceived as boring, indicating a reciprocal relationship. Future research should use longitudinal designs, in-situ assessments, and a more detailed measure of digital media activities to corroborate these findings and disentangle the direction of the effects.

Author contributions

ALC supervised the project; ALC performed the database and hand search; ALC and SM performed the screening, data extraction, and quality assessment; LM performed the meta-analysis; ALC wrote the first draft; SM and LM contributed to and revised the first draft; all authors revised and approved the final version.

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Declaration of competing interest

No conflict of interest to declare.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chbr.2023.100313.

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