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A systematic review of screen-time literature to inform educational policy and practice during COVID-19

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ABSTRACT

There is an urgent need for consensus around the matter of screen time (ST) during the COVID-19 pandemic. Some governments announced restrictions for online schooling time per day to protect students from perceived risks of prolonged screen-use, but critics and an emerging body of research question such regulations. Our review of 52 empirical studies found (a) an overwhelming majority of literature shows effect sizes too small to be of practical or clinical significance, and (b) findings more specifically on educational ST are inconclusive and critically underrepresented. These facts, along with the undeniable benefits of online learning in the absence of brick-and-mortar schooling and the ominous forecasts of learning loss caused by prolonged school closure, inform our recommendations for a more moderate policy and practical stance on restrictions - one that is focused on responsibly leveraging the educational and social benefits of ST in a world still recovering from the COVID-19 pandemic.

Introduction

The World Health Organization declared the outbreak of COVID-19 to be a global health emergency on 30th January 2020. One by one, countries enforced curfews, lockdowns, or shelter-in-place mandates in an attempt to curb the spread of the pandemic. By mid-April 2020, almost 200 country-wide school closures had taken place, affecting more than 1.5 billion or 90% of students globally (UNESCO, 2020). Public and private schools quickly mobilized and began setting up remote learning experiences for their students to prevent significant learning loss. However, as schools, teachers, students, and parents started to build familiarity and proficiency in their use of educational technology platforms, a concern slowly began to emerge over the potential physiological, psychological and academic risks associated between increased screen time (ST) and student wellbeing (Jarrett & Pomrenze, 2020; Shih & Killeen, 2020). ST implies any time spent engaged in screen-based activities such as watching TV or DVDs, using a computer or tablet for educational or recreational activities, playing video games, or using a cell phone to access the internet or social media applications (Hale & Guan, 2015; Schmidt et al., 2012; Xu, Wen & Rissel, 2015).

Concerns about ST existed even before the COVID-19 pandemic (Hirsh-Pasek, Evans & Golinkoff, 2019; Schaub, 2014), and may have been sparked by a body of prior research suggesting that ST might be associated with adverse physiological, psychological, and educational wellbeing outcomes such as obesity risk, inadequate sleep quantity and poor sleep quality, a higher risk of depression, and decreased academic performance, among many other problems (Adelantado-Renau et al., 2019; Carter, Rees, Hale, Bhattacharjee & Paradkar, 2016; Fang, Mu, Liu & He, 2019; Janssen et al., 2020; Liu, Wu & Yao, 2016; Wang, Li & Fan, 2019). Such findings might have led pediatric and child welfare organizations around the world to publish guidelines and recommendations limiting the daily use of ST (AAP Council on Communications & Media, 2016; Australian Government Department of Health, 2019; WHO, 2019). However, such recommendations were criticized for lacking a deep and nuanced-enough understanding of research findings, especially considering that ST literature is riddled with problems including the use of oversimplified definitions of ST, a lack of clarity between the relational direct of association between ST and associated indicators of wellbeing, the presence of confounding factors in studies, a lack of coherence and consistency in findings, and the finding of effect sizes being too small for clinical or practical use (Aarseth et al., 2017; Blum-Ross & Livingstone, 2016; Dienlin & Johannes, 2020; Drummond, Sauer & Ferguson, 2020; Odgers & Jensen, 2020; Straker, Zabatiero, Danby, Thorpe & Edwards, 2018; Tang et al., 2021).

While some organizations eventually tempered down their alarmist tone on the matter and reduced the prescriptiveness of their recommendations in light of scholarly criticism and emerging research, the rise in ST exposure during the COVID-19 pandemic (Ferguson, 2021)

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led old concerns to resurface in an amplified manner (Whiting, 2020; Winther & Byrne, 2020). Some governments even issued orders to schools restricting the number of hours of online classes allowed per day during pandemic lockdown, in an attempt to appease worried parents (Government of India - Ministry of Human Resource Development, 2020). However, at the other end, educators and scholars exhorted a more moderate and thoughtful approach - highlighting the educational and social benefits that technology might be able to offer at this difficult time (Nagata, Abdel Magid & Pettee Gabriel, 2021; Wiederhold, 2020). Conflicting positions have persisted for many years but there is a need for consensus now more than ever. In an attempt to resolve this dissonance, we undertook a systematic literature review driven by the research question - what do empirical findings from prior literature on the associations of ST with school-aged student wellbeing imply for policy, practice, and research in a post-COVID world? The end-goal of this systematic review was to present nuanced findings from scholarly literature to support policymakers, parents, and educators in establishing unity of vision and action on the matter of regulating educational ST engagement, during the COVID-19 pandemic recovery and recurrences or similar future emergencies.

Methodology

Given the inherent rigor and specific procedures involved in writing a systematic literature review (Okoli, 2015; Xiao & Watson, 2019) we referred to a range of expert guidelines to direct our methodology. In particular, a recently authored methodological guidance paper by Alexander (2020) was used to make decisions about the study's overall structure, framing of research questions, literature search and inclusion methods, coding and analytical procedures, and discussions or conclusions drawn from the findings.

Literature search and inclusion criteria

The systematic review began with an exploration of literature from multiple databases relevant to the topic via the EBSCOhost platform, including Academic Search Ultimate, Applied Science & Technology Full Text (H.W. Wilson), Child Development & Adolescent Studies, Education Full Text (H.W. Wilson), Education Source, ERIC, Health Source - Consumer Edition, APA PsycArticles, APA PsycInfo, and Teacher Reference Center. The search terms used were "screen time", "screen-time", "active screen time", "active screen-time", "educational screen time", "educational screen-time", "online learning", "online learning environment", "mobile devices", "distance education", "blended learning", "computer use", "computer-assisted learning", "computer assisted learning", "virtual learning", "flipped classroom", "E-learning", "web-based learning", and "learning management system".

Five criteria were identified based on which studies would be included in the literature review. The inclusion criteria were guided by the research question (Xiao & Watson, 2019) and inspired by existing systematic reviews (Quin, 2017; Schott, van Roekel & Tummers, 2020).

1 *Relevance* - Only studies that were a good fit with the research question were included. This implied that studies must explicitly explore the relationship between time spent on any screen and some measure of student outcomes. Studies where ST was a mediating variable and the independent variable was another construct, and studies that treated ownership of devices as the independent variable instead of time spent engaging with screens, were excluded. Studies that did not specify the measure of ST used were also excluded.

2 *Participants* - Studies included school-aged (6–17 year old) participants, because the main goal of the study was to fill the gap in previous literature and also address the issue of ST during school at home. Studies that investigated effects on participants once they crossed school going age were excluded. Studies focused on participants diagnosed with special needs or participants clinically diagnosed with device-based or internet-based addictions or pathological use of the internet and ST were excluded, because these populations were associated with specialized interventions and represented a very small proportion of the school-going population. Considering the limited scope of this study, we decided to focus on typically developing populations.

3 *Study Design* - The literature included only empirical studies and avoided theoretical studies, because the goal of the review was to investigate empirical findings on ST. Additionally, meta-analyses and literature reviews were excluded to avoid duplication of studies. Studies where ST was a joint measure with some other variable, or where ST was reported as a moderating or dependent variable in regression analysis were excluded because our inquiry was focused on the ways that ST as an independent variable might be influencing student well-being. Studies that did not report p values for statistical significance were excluded, as were studies that did not report any measure of variance such as confidence intervals or standard errors that might allow us to assess the reliability of findings. Studies that did not report effect sizes between associations presented were also excluded because effect size is considered to be one of the most important findings in empirical studies and must be presented along with calculations of statistical significance (American Psychological Association, 2010; Lakens, 2013). Pearson's r was adopted as the standardized measure of effect size for our literature review considering its appropriateness for correlational studies (Durlak, 2009; Funder & Ozer, 2019), and hence studies whose effect sizes were expressed in metrics that could not be converted into r values or did not provide sufficient raw data that we could use to independently compute r values were excluded.

4 *Year of Publication* - Only articles published since 2010 were included, because technology-related fields are exceptionally dynamic and we wanted to ensure this study addressed the most updated and currently relevant screen-time platforms and media.

5 *Type of Publication* - Only peer-reviewed studies were included, in order to ensure a high level of credibility in the literature.

Study selection

In total, a corpus of 1486 studies were collected as of 25th October 2021. Next, the *content analysis* method was used to filter the studies by identifying the main ideas, themes and methods presented (Hsieh & Shannon, 2005; Mayring, 2004). To this end, two of the authors independently reviewed the titles and abstracts of the papers to remove duplicates and ensure that studies showed a good fit with the research question using the five criteria outlined in the previous section. Full texts were studied in cases that were unclear. The two authors discussed their findings, and keeping the agreed upon criteria in mind, established consensus over including only 52 of the studies for in-depth review (Figure 1).

Coding process

All three of the authors were involved in the coding process. In order to code the articles selected for the review, an Excel-sheet was made to facilitate the organization of findings in a systematic way. A mix of deductive and inductive coding approaches were used to code the studies. Deductive coding is where predetermined codes are identified and used to code the data (Linneberg & Korsgaard, 2019). Deductive coding was used to categorize studies based on sample size, geographical location, participant ages, statistical analysis methods used, and relevant findings about the outcomes of ST. Inductive coding is emergent, and codes are created by studying the research rather than basing codes in existing data sets of research (Linneberg & Korsgaard, 2019). Inductive coding was used to categorize types of ST because the extant literature did not define such a categorization based on the content and context of ST use.

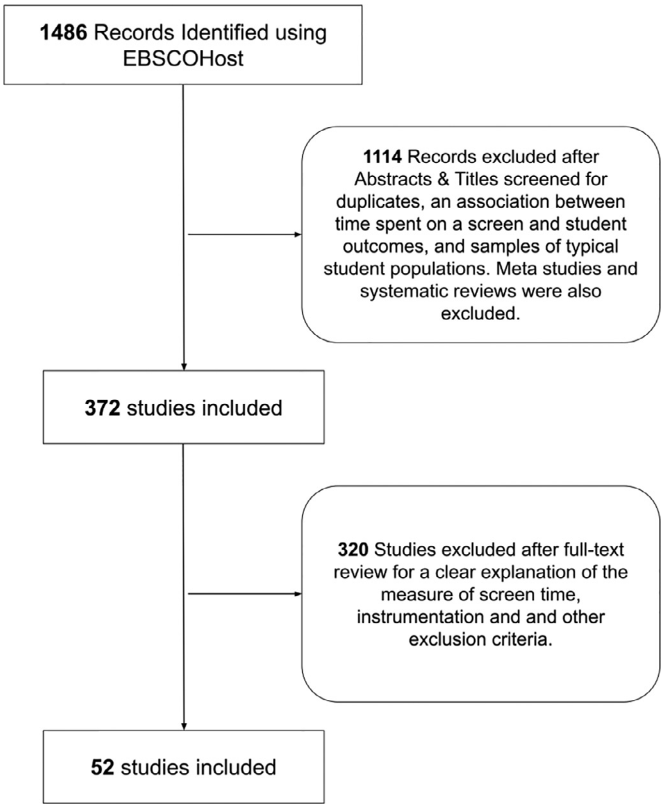

Fig. 1. Flow Diagram of Literature Selection Strategy.

This categorization emerged only as the authors explored the literature themselves.

The inductive coding process revealed five categorizations or types of ST from the literature, based on how the authors defined and measured ST. The first type of ST related to watching television while being physically sedentary. This was categorized as *passive viewing ST*. The second type was *gaming ST,* which referred to activities like playing video games, computer games, or games on portable devices like smartphones or tablets - and were either physically sedentary or physically active. The third type of ST was *socio-recreational ST,* which pertained to using a computer or mobile device for social networking, chatting, tweeting, surfing the internet for leisure, texting, emailing and other unspecified leisure activities. The fourth type of ST was *educational ST,* which involved the use of a computer or other portable device for educational purposes like schoolwork, studying, or doing homework. Finally, the fifth type of ST was *total* ST - a generic measure achieved by combining two or more types of ST and examining their collective associations with psychological, physiological, or educational outcomes. Total ST studies often collected data on distinct types of ST separately, but always mixed the data before any analysis and reported total ST as the combined hours or time spent on any and all types of screen-based activities including watching television, playing video games, using social media, doing homework, texting friends, and any others.

Quality appraisal

Given that all the studies in our literature pool were quantitative in nature, a checklist (Annexure A) developed by Kmet, Cook and Lee (2004) was used to assess the methodological quality of the literature under review. The checklist was accompanied by a detailed scoring instructions manual and rubric to ascertain the extent to which quality indicators were met or not (0 = "no", 1 = "partial", 2 = "yes"). A quality score was then calculated for each study by adding the scores obtained across all quality indicators and dividing the sum by the maximum possible points. All three researchers studied the assessment rubric and then rated one randomly chosen study from the literature pool together, in order to establish a shared understanding of the criteria and scoring instructions prior to the coding process. Subsequently, two of the authors independently coded all the remaining studies from the final literature pool. Items 5, 6, 7 and 12 on the checklist were only relevant for studies that used randomized allocation and were experimental in nature, but none of the studies in the literature pool met this criteria and hence the items were marked as "NA" or not applicable, as per instructions provided in the scoring manual for this checklist (Kmet et al., 2004).

The studies achieved mean quality scores ranging from 0.85 to 0.95, indicating that all of them were of a very high quality (Kmet et al., 2004). Levels of absolute percentage agreement and Cohen's Kappa were calculated to establish interrater reliability (McHugh, 2012; Park & Kim, 2015) between the coders. In terms of absolute percentage agreement, the studies ranged from 70% to 100% agreement, with all but two of the studies having agreement levels of 90% or more. The average Kappa score across studies was 0.86 indicating a high degree of interrater reliability (Graham, Milanowski & Miller, 2012; McHugh, 2012). Additional details about item-wise ratings by each rater, mean quality scores, percentage agreement levels, and Kappa levels can be found in Supplementary Materials S2.

Measures and analysis

The effect sizes in our literature pool have been reported in terms of several different measures, including odds ratios, standardized regression coefficients (beta), R-squared, and Cohen's d. In order to compare the size of effects across these studies we transformed them into one singular measure - Pearson's r. We chose Pearson's r as the singular unifying measure for our literature review because it is considered one of the most widespread and appropriate measures of effect size for correlational studies (Durlak, 2009; Funder & Ozer, 2019). In studies where standardized regression coefficients were reported, and no raw data was available, we imputed Pearson's r using Peterson and Bown's (2005) formula of $r = .98\beta + .05\lambda$. This approach has been used by several peer-reviewed metastudies over the years including recent ones (Barari, Ross, Thaichon & Surachartkumtonkun, 2021; Compas et al., 2017; Robson, Allen & Howard, 2020; Vasconcellos et al., 2020). In cases where odds ratios or d values were reported, we used the conversion formulae suggested in recent literature on meta-analytic methodologies (Borenstein, Cooper, Hedges, & Valentine, 2009; Polanin & Snilstveit, 2016); to compute the Pearson's r values. Finally, in studies that reported R-squared, we simply calculated square roots for each of the reported effect sizes to convert them into Pearson's r values.

Results and discussion

Study characteristics

The final pool of studies included were from a wide range of geographical contexts across the world. The data collected as part of these studies were taken from 93 samples in 45 different countries. Males and females were more or less equally represented with male participants composing 50.5% of the average sample and their female counterparts composing an average 49.5%. The studies varied extensively in terms of sample sizes, with some using samples as large as n = 200,615 and others using samples as small as n = 98 participants. With regard to age, 23 studies (44.2%) included participants aged 6 to 10 years, 47 studies (90.4%) included 11 to 13 year olds, and 38 studies (73.1%) included 14 to 17 year olds. Additionally, 13 studies (25%) included participants ranging from 17 to 20 years old, and were included because their sample sets had students of the age 17 years which was the outer cut off age in our inclusion criteria.

In terms of research design, 39 studies (75%) used cross-sectional research designs, while 12 studies (23.1%) were longitudinal and one study (1.9%) used a combination of a cross-sectional as well as longitudinal design. Amount of ST was measured via parent or student self-reports across all studies, and only one study (1.9%) explicitly related to ST use at school. Participants stated the frequency and duration of their engagement with various screen-based activities through surveys, interviews and time diaries. All the studies employed quantitative research designs, relying on statistical methods for data analysis including correlation coefficients, chi-square tests, ANCOVA, T-tests, ANOVA, Mann-Whitney test or Wilcoxon rank-sum test, Cohen's d, and different types of regression analysis among others. See Supplementary Materials S1 for details on study characteristics.

Types of ST

Five distinct categorizations of ST emerged from the literature. The first type of ST was *passive viewing ST*, which featured in 17 studies (32.7%) in the literature pool. The second type was *gaming ST,* which featured in 13 studies (25%) in the literature pool. The third type of ST was *socio-recreational ST,* which was addressed by 10 studies (19.2%) in the literature pool. The fourth type of ST was *educational ST,* and only two studies (3.8%) in the literature pool addressed it directly. To summarize, the majority of ST research is focused on television viewing and video games while the use of screens for educational purposes is significantly underrepresented and neglected. Additionally, a total of 42 studies in the literature pool (80.8%) measured ST in terms of *total* ST engagement by combining multiple ST types together and measuring their collective associations with the dependent variables under study. See Supplementary Materials S1 for studies associated with each type of ST and detailed findings from each individual study that was part of the final literature pool.

Key findings from the literature

Details of findings across all types of ST can be found in Supplementary Materials S1. A synthesis of findings from the studies and their relation to prior research are presented in this section.

Size of effects

Majority of the findings from the final literature pool presented statistically significant associations between ST and variables related to psychological, physiological, or educational wellbeing of the participants. However, statistical significance alone is not a sufficient measure for findings and instead it must be accompanied by information on the size of the effects found (American Psychological Association, 2010; Durlak, 2009; Kline, 2004; Lakens, 2013; Schäfer & Schwarz, 2019; Sullivan & Feinn, 2012). While statistical significance confirms whether or not differences between two groups are due to chance, effect size explains the magnitude of the difference between variables of interest across groups (Durlak, 2009; Funder & Ozer, 2019; Kelley & Preacher, 2012; Schäfer & Schwarz, 2019; Sullivan & Feinn, 2012). Presenting effect sizes is critical because in a sufficiently large sample one will almost always find statistically significant differences between variables, but it is the magnitude of these differences that determines their practical or clinical utility (Sullivan & Feinn, 2012).

Qualifying the size of effects is a complicated matter because no universally agreed upon relationship between effect sizes and their practical or clinical utility exists (Bosco, Aguinis, Singh, Field & Pierce, 2015; Durlak, 2009; Ferguson, 2009; Ferguson & Heene, 2021; Funder & Ozer, 2019; Hill, Bloom, Black & Lipsey, 2008). While attempts have been made to create objective cut off points to qualify the significance of effect sizes, most prominently by Cohen (1988), researchers have repeatedly expressed that any cut offs should be treated as nothing more than rough guidelines (Cohen, 1988; Drummond et al., 2020; Ferguson & Heene, 2021). Effect sizes in the field of social science research warrant great caution when drawing inferences to inform policy or practice because they may be statistically significant but if they are too small in size then they might not imply any relevant associations between the variables under study (Ferguson & Heene, 2021; McCartney & Rosenthal, 2000). Recent studies show that a surprising number of nonsensical associations may achieve statistical significance with effect sizes that pass the lower end of traditional cut off points but this does not make the associations practically or clinically useful (Ferguson & Heene, 2021; Orben & Przybylski, 2019). Further, there are concerns over publication bias in the field of psychology where there is an aversion to transparency with regard to the extent of null findings in a study's sample, leading to an unduly high prevalence of findings that support associations or hypotheses which may not actually exist in reality (Chambers, 2019; Earp & Trafimow, 2015; Ferguson & Heene, 2021; Kühberger, Fritz & Scherndl, 2014; Plonsky & Oswald, 2014).

When considering valid cut offs for effect sizes it is necessary to be sensitive to the unique context of the study and engage in a cost-benefit analysis that supports decision making for practical and clinical purposes (Durlak, 2009; McCartney & Rosenthal, 2000; Plonsky & Oswald, 2014). The historically unique context of our study - the COVID-19 pandemic - was an important consideration in our evaluation. The undeniable educational, social, and recreational benefits of technology use by children during these exceptional times (Nagata et al., 2021; Wiederhold, 2020), and the potentially high loss of student learning estimated due to school closures (Banerji & Wadhwa, 2021; Kuhfeld & Tarasawa, 2020), were important criteria to consider. The stakes were high and hence findings on the harms of ST exposure would need to be relatively high in magnitude to contend with the benefits of ST during these exceptional times. This led us to adopt a minimum cut off threshold that minimized the chance of ascribing significance to relationships with effect sizes so small that it would be difficult to confidently ascribe them as *true* effects free of noise from methodological flaws, biased misrepresentations or misinterpretations of findings, and many other concerns that have been raised by researchers regarding very small effect sizes (Drummond et al., 2020; Ferguson & Heene, 2021). To this end, we have considered a threshold of $r = 0.10$ as the minimum magnitude of association that supports a hypothetical relation between variables and $r = 0.20$ as the minimum value to suggest any potential for clinical or practical significance (Bosco et al., 2015; Drummond et al., 2020; Ferguson & Heene, 2021).

Across all studies in our literature pool, 44.19% of the findings fell between $r = 0$ to $+/-0.10$, and 34.88% of findings fell between $+/-0.10$ to $+/-0.20$. Taken together, 79.07% of the findings fell below $r=+/-0.20$ which implied the effects were either too small to be considered hypothesis supportive or so small that they were not practically or clinically useful. Only 17.15% of the findings had effects between the sizes of $r=+/-0.2$ to $+/-0.3$, implying a clinically or practically relevant but weak association, and only 3.49% of the findings showed moderate to larger effects between $r=+/-0.3$ to $+/-1.0$ (Fig. 2). Overall, an overwhelming majority of the studies found effect sizes either too small for practical or clinical utility, or having very weak effects. It is important to bear this in consideration while perusing subsequent sections in order to avoid misinterpreting findings. Small effect sizes have been flagged as a critical issue in previous ST literature too (Adelantado-Renau et al., 2019; Dienlin & Johannes, 2020; Ferguson, 2021; Odgers & Jensen, 2020; Stiglic & Viner, 2019; Wang et al., 2019).

Total ST was almost always negatively associated with student wellbeing

A statistically significant inverse association was found between total ST and measures of physiological well-being across several studies, echoing findings from previous metastudies (Hale & Guan, 2015; Liu et al., 2016; Stiglic & Viner, 2019; Wang et al., 2019). Studies showed associations between total ST and sleep-related issues such as poor sleep quality, lesser sleep duration, daytime sleepiness, and insomnia related symptoms (Hardy, Ding, Peralta, Mihrshahi & Merom, 2018; Kubiszewski, Fontaine, Rusch & Hazouard, 2014; Lange et al., 2017; McManus, Underhill, Mrug, Anthony, & Stavrinos, 2021; Steele, Richard-

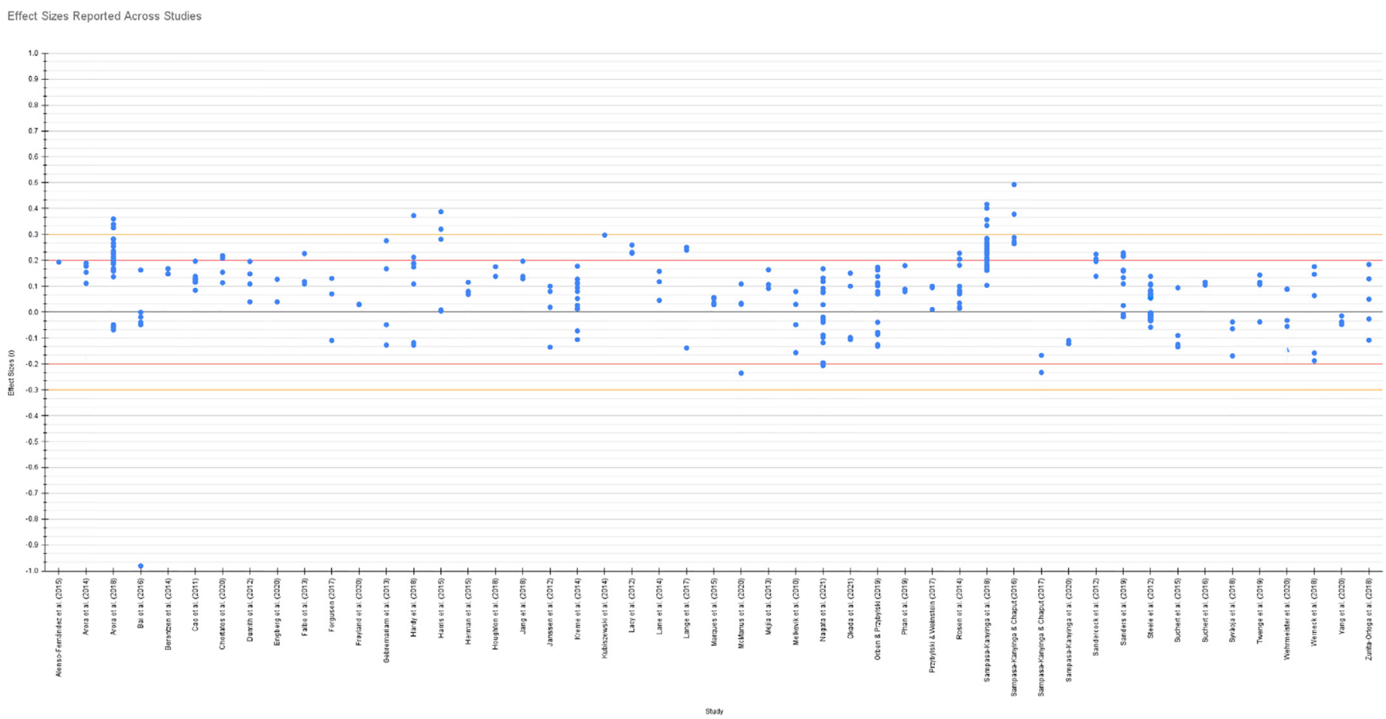

Fig. 2. Effect sizes found across studies.

son, Daratha & Bindler, 2012; Syväoja et al., 2018; Twenge, Hisler & Krizan, 2019; Wehrmeister et al., 2020). Further, a number of studies showed an association between total ST and an increase in body fat, BMI, obesity, and weight-related issues (Bai et al., 2016; Berentzen et al., 2014; Dumith, Garcia, da Silva, Menezes & Hallal, 2012; Falbe et al., 2013; Jang et al., 2018; Mejía et al., 2013; Sanders, Parker, del Pozo-Cruz, Noetel & Lonsdale, 2019; Suchert, Hanewinkel & Isensee, 2016). Similarly inverse associations were found between total ST and dietary choices and other global indicators of physical health (Herman, Hopman & Sabiston, 2015; Lacy et al., 2012; Nagata et al., 2021; Sampasa-Kanyinga & Chaput, 2017; Sanders et al., 2019). On the other hand, Suchert et al. (2016) and Engberg, Figueiredo, Rounge, Weiderpass and Viljakainen (2020) found no significant association between total ST and waist-to-height ratios or waist circumference, and Porter, Matthews, Salvo and Kohl (2017) found no significant association between total ST and cardiovascular function.

Studies also found a statistically significant association between total ST and lower physical activity (Alonso-Fernández, Jiménez-García, Alonso-Fernández, Hernández-Barrera & Palacios-Ceña, 2015; Melkevik, Torsheim, Iannotti & Wold, 2010; Sandercock, Ogunleye & Voss, 2012; Syväoja et al., 2018; Zurita-Ortega et al., 2018). However, one study found no association between total ST and physical fitness (Aires et al., 2010). Some studies found that school and home computer exposure were associated with computer-related musculoskeletal soreness and physical health complaints such as headaches, back pain, and sleep irritability (Harris, Straker, Pollock & Smith, 2015; Marques, Calmeiro, Loureiro, Frasquilho & de Matos, 2015; Werneck et al., 2018).

Findings were consistent about total ST being associated with adverse psychological indicators like conduct problems, violence, bullying, depression, self-esteem issues, and risky behaviours such as intake of tobacco and alcohol (Cao et al., 2011; Ferguson, 2017; Frøyland, Bakken & von Soest, 2020; Herman et al., 2015; Houghton et al., 2018; Janssen, Boyce & Pickett, 2012; Kremer et al., 2014; Okada, , Isumi & Fujiwara, 2021; Orben & Przybylski, 2019; Rosen et al., 2014; Sampasa-Kanyinga et al., 2020; Sanders et al., 2019; Suchert, Hanewinkel & Isensee, 2015; Werneck et al., 2018). One of these studies found a negative association between total ST and depression, self-esteem, self-concept of physical attractiveness and general self-efficacy to be significant for girls while for boys a significant association was only found with self-esteem (Suchert et al., 2015). However, one study found that meeting ST guidelines was not associated with flourishing or well-being (Faulkner, Weatherson, Patte, Qian & Leatherdale, 2020) and another found no significant association between total ST and self-concept (Suchert et al., 2016). Additionally, Yang et al. (2020) clubbed time spent online and on video games found that less than three hours of total ST per week was positively associated with social development. Finally, with regard to the relationship between total ST and educational outcomes, studies were consistent in finding an association between ST and unfavorable outcomes like decreased academic performance (Ferguson, 2017; Sanders et al., 2019; Syväoja et al., 2018) and dissatisfaction in school life (Cao et al., 2011).

While a majority of the findings presented showed statistically significant associations between ST and indicators of student well being, it is important to consider the weak magnitude of their reported effect sizes. A total of 82.35% findings fell under our minimum cut off effect size of $r=+/-0.20$, not qualifying them as hypothesis supportive or practically or clinically useful. Only 14.44% qualified, but even these fell only within the small effect size range of $r=+/-0.20$ to $+/-0.30$, while only 3.21% reported moderate and above effect sizes of more than $r=+/-0.30$ (Fig. 3).

Non-Educational st was mostly negatively associated with student wellbeing

From studies in our literature pool that explored passive viewing ST, almost all showed unfavorable associations with a variety of physiological, psychological, and educational outcomes for the users, including sleep and physical health, physical activity, psychological well-being, social communication, and academic achievement (Arora, Albahri, Omar, Sharara & Taheri, 2018, 2014; Berentzen et al., 2014; Chortatos, Henjum, Torheim, Terragni & Gebremariam, 2020; Engberg et al., 2020; Falbe et al., 2013; Gebremariam et al., 2013; Lane, Harrison & Murphy, 2014; Melkevik et al., 2010; Nagata et al., 2021; Przybylski & Weinstein, 2017; Sanders et al., 2019; Yang et al., 2020). This supports findings from prior systematic literature reviews

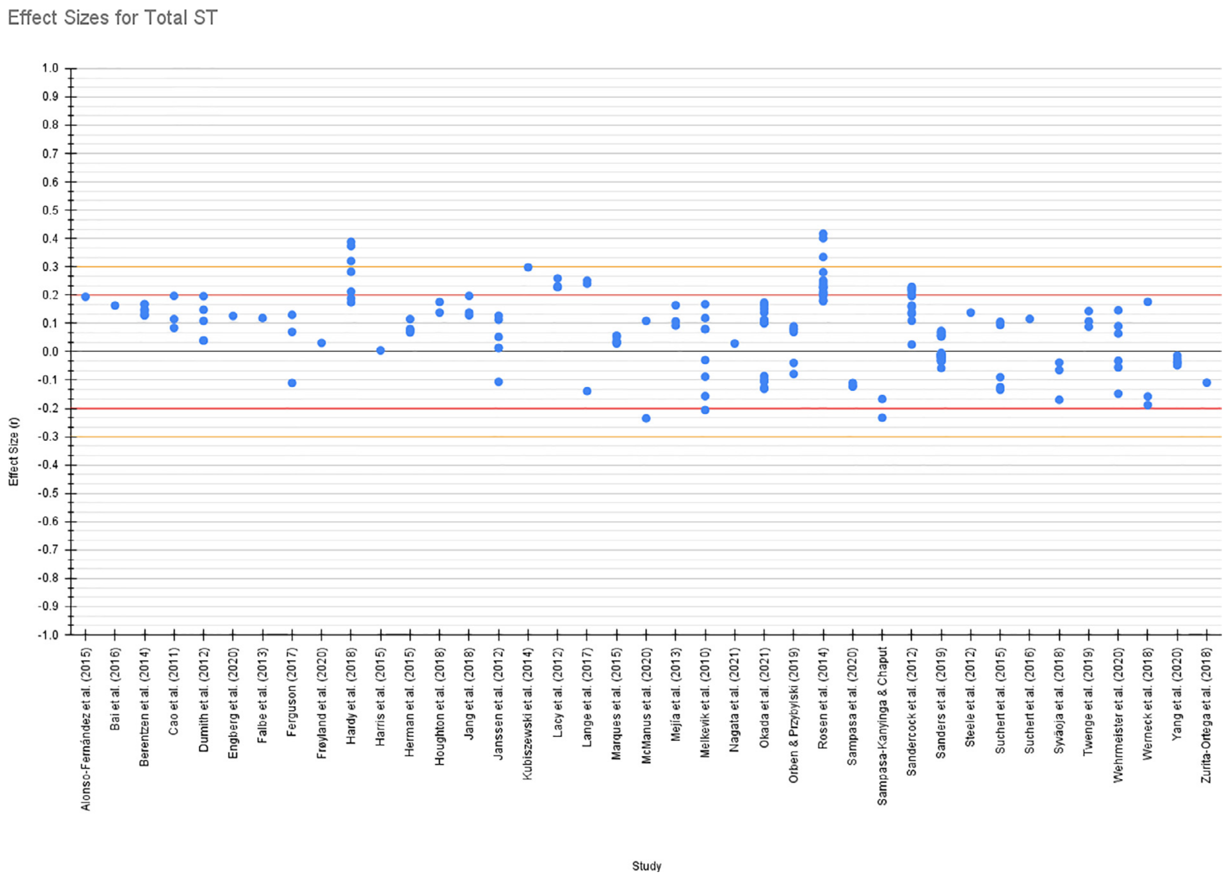

Fig. 3. Effect sizes for Total ST.

and meta-analyses (Adelantado-Renau et al., 2019; Fang et al., 2019). However, Falbe et al. (2013) only found a negative association with BMI with TV watching but not video and DVD viewing. Additionally, one study found no significant associations between passive ST and depression (Houghton et al., 2018), another found no significant associations with health complaints (Marques et al., 2015), and Jang et al. (2018) found no association with BMI.

With regard to gaming ST, some studies found unfavorable associations with health-related and psychological well-being indicators including trouble with sleep, obesity, poor dietary choices, peer problems, physical activity and poor mental health among others (Arora et al., 2018, 2014; Chortatos et al., 2020; Falbe et al., 2013; Gebremariam et al., 2013; Janssen et al., 2012; Lange et al., 2017; Melkevik et al., 2010; Phan et al., 2019; Przybylski & Weinstein, 2017; Rosen et al., 2014; Sanders et al., 2019). On the contrary, one study found a small positive association between gaming ST's associations and educational outcomes (Sanders et al., 2019). A few studies did not find significant associations between gaming ST and any binge-eating disorder (Nagata et al., 2021), depression (Houghton et al., 2018), BMI (Jang et al., 2018) or health complaints (Marques et al., 2015). Prior metastudies related to gaming ST and user outcomes were similarly conflictive over outcomes. While some studies showed direct associations with physical aggression (Prescott, Sargent & Hull, 2018) and reduced educational outcomes (Adelantado-Renau et al., 2019), other studies found increased cognitive development (Bediou et al., 2018), positive psychological outcomes (Andrade, Correia & Coimbra, 2019), promotion of light-to-moderate physical activity (Peng, Lin & Crouse, 2011), and no *true* effects between gaming and aggression (Drummond et al., 2020),

Some studies found that socio-recreational ST was associated with poorer sleep, physical activity, binge eating, and other physiological indicators (Arora et al., 2014; Nagata et al., 2021; Rosen et al., 2014; Sampasa-Kanyinga, Hamilton & Chaput, 2018). However, one study did not find an association between socio-recreational ST and physical activity (Chortatos et al., 2020). Studies also showed unfavorable associations with academic performance and mental health issues like depression, conduct problems, higher incidence of risk behaviours including physical fighting, and low overall social quality of life (Arora et al., 2018; Frøyland et al., 2020; Houghton et al., 2018; Przybylski & Weinstein, 2017; Sampasa-Kanyinga & Chaput, 2016; Sanders et al., 2019). Prior metastudies support these findings, with studies showing associations between social media use and negative psychological outcomes (Sohn, Rees, Wildridge, Kalk & Carter, 2019; Yoon, Kleinman, Mertz & Brannick, 2019). However, one study did not find significant associations between socio-recreational ST and depression (Houghton et al., 2018).

While several of the findings above showed statistically significant associations between ST and indicators of student well being, it is important to consider the weak magnitude of their effect sizes. A total of 75.38% findings fell under our minimum cut off effect size of r=+/−0.20, not qualifying them as hypothesis supportive or practically or clinically useful. Only 19.23% qualified but fell within the small effect size range of r=+/−0.20 to +/−0.30, and only 5.38% reported moderate and above effect sizes of more than r=+/−0.30 (Fig. 4).

Educational ST studies were underrepresented and findings were inconclusive

There was a gross underrepresentation of studies that separated the effects of educational content related ST from the effects of other non-educational ST. Only two studies in our literature pool (3.8% of total studies) measured educational ST, in comparison to 50 studies (96.2% of total studies) that measured some form of non-educational ST or total ST. The two studies on educational ST showed mixed results. One study found that engagement with educational ST, especially close to bed time,

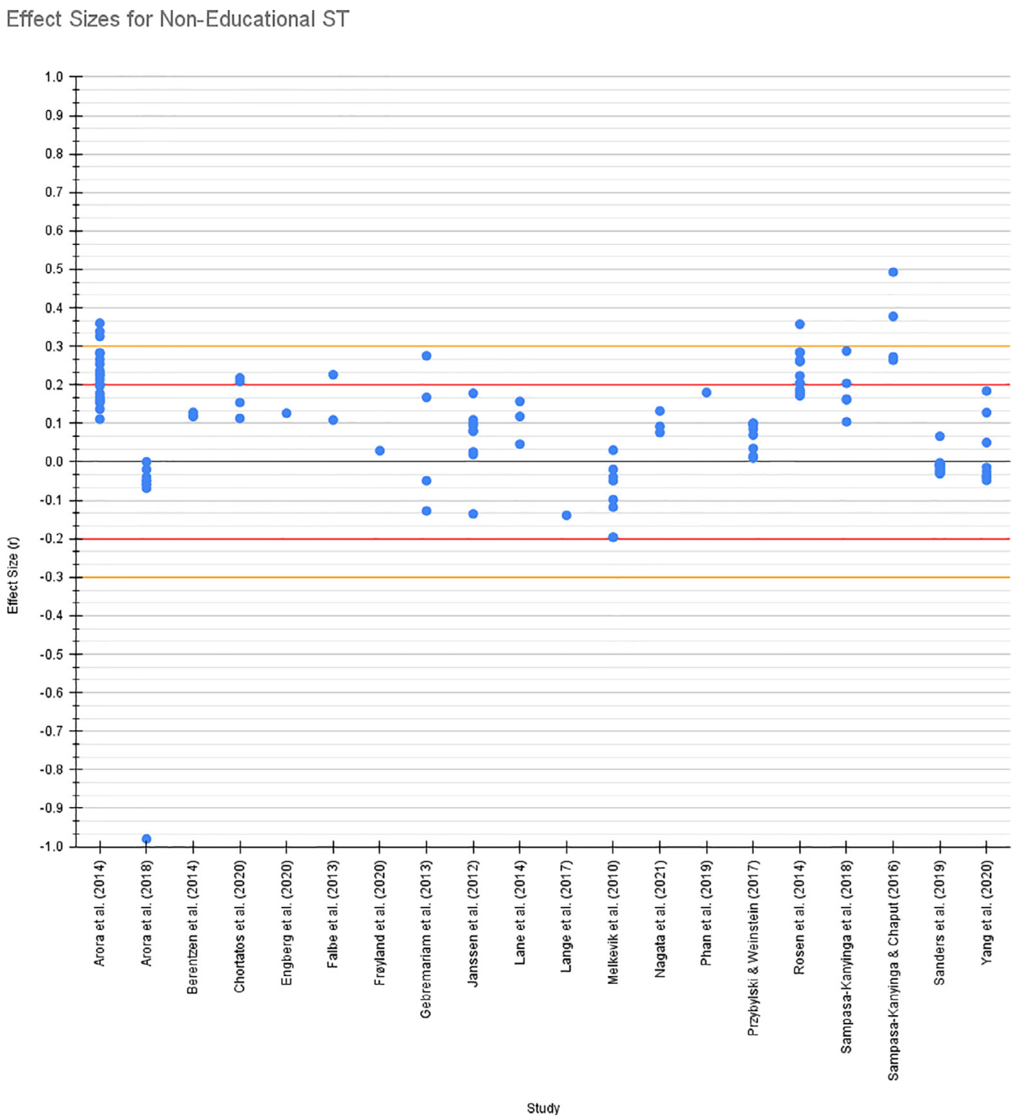

Fig. 4. Effect sizes for Non-Educational ST.

negatively affected sleep outcomes (Arora et al., 2014). However, four out of five findings reported in this study showed effect sizes below our minimum cut off point of r=+/−0.20 thereby not qualifying them as hypothesis supportive or practically or clinically useful, while one finding reported $r = 0.210$ implying an extremely small effect size. Further, the study's statistically significant association between educational ST and sleep was not supported by any previous studies or literature reviews. The second study asserted that no negative psychological or physiological associations were experienced by users, and instead a significant positive association was found with educational outcomes (Sanders et al., 2019). However, the effect sizes of the 11 reported findings were all below our minimum cut off point of r=+/−0.20 and thereby not qualifying them as hypothesis supportive or practically or clinically useful. The finding that educational ST was statistically significantly associated with positive educational outcomes was supported by a recent meta-study by Madigan, Racine and Tough (2020), which found relationships between educational content engagement and increased cognitive abilities in preschool-aged children.

Displacement hypothesis and bidirectional associations

Several studies that found unfavorable associations between ST and variables related to student well-being, suggested that the negative association may have been caused due to the *displacement hypothesis* (Dumith et al., 2012; Gebremariam et al., 2013; Hardy et al., 2018; Houghton et al., 2018; Lacy et al., 2012; Sampasa-Kanyinga et al., 2018; Sandercock et al., 2012; Syväoja et al., 2018). The displacement hypothesis explains that the ill effects of time spent on screens are caused when screen use displaces other productive activities such as socializing with peers, sleep, time spent on homework and physical activities to name a few (Neuman, 1988; Przybylski & Weinstein, 2017). For example, if a child watches television for a few hours every evening because of which she does not go outside and play with her friends, then her overall physical activity will reduce which might in-turn unfavorably influence health related parameters like BMI. In such a case, time watching television is not directly influencing BMI, but instead indirectly influencing it because television time here is directly influencing physical activity time which is then influencing BMI. The mediating variable here is physical activity. So, hypothetically speaking, if the child watched TV at some other time in the day and if she went out and played with her friends in the evening anyway then maybe her BMI would not be an issue at all. While several studies from the literature pool suggested that similar displacements might have been at play, none of them actually measured whether ST was in fact displacing critical activities. The absence of empirical support for this hypothesis has been highlighted in prior literature too (Marshall, Biddle, Gorely, Cameron & Murdey, 2004; Przybylski, 2019; Przybylski & Weinstein, 2017; Valkenburg & Peter, 2007).

Also, some studies in our literature pool (Houghton et al., 2018; Kremer et al., 2014; Syväoja et al., 2018) explored the bidirectional nature of association between ST and wellbeing indicators i.e. they explored the potential of not only ST's influence on wellbeing but also the influence of wellbeing on ST exposure. While the findings across these studies taken together do not provide any conclusion on the matter, researchers have expressed the need for more studies to determine such associations (Gunnell et al., 2016; Kim, Umeda, Lochbaum & Sloan, 2020; Kremer et al., 2014; Magee, Lee & Vella, 2014; Zink, Belcher, Kechter, Stone & Leventhal, 2019).

Empirical studies on st had several research design limitations

One of the most important findings from the review of literature was that studies on ST had several limitations in their research methodology. To begin with, the absence of experimental design prevented the possibility of causal claims being drawn and exposed the studies to several threats of validity (Shadish, Cook & Campbell, 2002). This concern has been echoed in prior literature (Adelantado-Renau et al., 2019; Hale & Guan, 2015; Janssen et al., 2020). Also, most studies did not control for moderating variables such as parent influence, dietary habits, the time of day during which the devices were used, and most importantly the displacement of desirable activities like sleep, socialization and exercise, thereby confounding the results. This is an issue echoed in previous literature on ST as well (Adelantado-Renau et al., 2019; Fang et al., 2019; Lanca & Saw, 2020).

A majority of studies did not separate the different types of ST and precisely measure the association of each type with physiological, psychological, and educational outcomes for the user. Instead, studies predominantly explored a generic measure of *total ST* where passive viewing ST, socio-recreational ST, and gaming ST, along with one educational activity were thrown into a mix to create a consolidated measure of ST. These studies defined ST as time spent engaged in any screen-based activity for any purpose (Hale & Guan, 2015; Janssen et al., 2020; Stiglic & Viner, 2019), and such a definition is problematic because it wrongly assumes that all kinds of ST have the same influence on a child without considering the nature of screen-use (Madigan et al., 2020; Sweetser, Johnson, Ozdowska & Wyeth, 2012; Yang, Chen, Wang & Zhu, 2017; Zimmerman & Christakis, 2007). Such studies oversimplified the construct of ST, ignoring the potentially distinct influence of ST-engagement content and context, among other moderators, on wellbeing (Blum-Ross & Livingstone, 2016; Lissak, 2018; Madigan et al., 2020; Stiglic & Viner, 2019; Straker et al., 2018; Sweetser et al., 2012; Yang et al., 2017; Zimmerman & Christakis, 2007). Further, even studies that did try to establish more precise categorizations of ST did not sufficiently address the context and content of ST under investigation. For example, several papers explored "computer use" time as the measure of ST without clarifying if the computers were used for passive watching engagements, educational work, gaming, or socio-recreational activities. This is a serious limitation, because prior literature has repeatedly found that the content and context of screen-use might influence the nature and extent of its association with user outcomes (Adelantado-Renau et al., 2019; Fang et al., 2019; Stiglic & Viner, 2019; Straker et al., 2018). Finally, studies used self-report measures by parents or students to assess time spent on screens, and in ng so these studies were exposed to serious measurement error, bias, and inaccuracies in recollection (Aires et al., 2010; da Silva, Menezes, Wehrmeister, Barros & Pratt, 2017; De Jong et al., 2012; Hale & Guan, 2015; Lanca & Saw, 2020).

Conclusion

Our research question was, "what do findings from prior literature on the associations of ST with school-aged student wellbeing imply for policy, practice, and research in a post-COVID world?" To begin with, the findings must be interpreted with great caution, considering the many limitations in the research design of available studies and the overwhelmingly trivial and small effect sizes reported across a majority of studies that make it difficult to separate true effects from noise. Also, the disparity in volume and findings between educational ST and the other non-educational types of ST should caution readers to pay more attention to the content and context of ST when attempting to draw inferences to inform policy or practice. Lumping educational ST along with the other types of ST leads to an overgeneralization that focuses squarely on time consumption and "ignores the issue that how media are used is often more critical than how often media are used" (Ferguson, 2017, p. 803).

Empirical evidence has previously shown the damage that can be done to student learning because of extended breaks from schooling, for example *summer slide* - the phenomenon where students are found to have lost significant learning after returning from their summer vacations (Alexander et al., 2016; Cooper, Nye, Charlton, Lindsay & Greathouse, 1996). Extending the summer slide projections to simulate what might happen if schools remain closed for even longer periods of time due to COVID-19 shows the potential for serious negative effects on student learning (Kuhfeld & Tarasawa, 2020). A recent report by Pratham - India's largest educational NGO - showed a clear drop in pre-pandemic and post-pandemic basic literacy performance in elementary grade students in rural India where access to technology was a problem (Banerji & Wadhwa, 2021). The high risk of learning loss because of school closures cannot be ignored, and neither can the benefits of increased ST during at this time - whether it be for educational purposes, socialization, or even for recreational engagement of children thereby allowing adults in the household to continue remote or on-site work (Nagata et al., 2021; Wiederhold, 2020; Wong et al., 2021). To this end, we echo the sentiments of Ferguson (2017) and recommend to governmental and non-governmental health organizations that "adopting a more moderate and measured tone" is needed with policy statements (p. 803).

For parents and educators, we suggest that, "it is time to move beyond a heavy focus on risk with little exploration or recognition of opportunities" (Blum-Ross & Livingstone, 2016, p. 27), and instead leverage the strengths and benefits of ST in a purposeful way while mitigating any associated risks during these exceptional times (Nagata et al., 2021; Straker et al., 2018; Wiederhold, 2020). A majority of the ST studies that found negative associations with user outcomes were often mediated by activity that happens before or after school hours where such ST displaced time for physical exercise, sleep, and social interaction, and hence we caution that educational ST engagements during the pandemic should be careful not to displace such important activities. Families concerned about over-exposure to ST, can use discretion to establish guidelines to limit their children's exposure to non-educational ST and thus reduce total ST during this period (Wong et al., 2021). While concerns about ST's impact on poor eyesight may be laid to rest by recent studies (Lanca & Saw, 2020), and the authors could not find any empirical evidence to associate ST with long term musculoskeletal damage, parents and teachers are nevertheless encouraged to help students take precautions to reduce eye strain, maintain healthy posture, and avoid poor eating and sleep habits during online schooling in the pandemic. This can be done by promoting the use of simple strategies freely available on pediatric and government online resources (for example, Hirsh-Pasek et al., 2019; Lee, 2016).

Limitations and recommendations for future research

A set of limitations were experienced due to the strict search parameters used in our study. Literature included was confined to only that published in peer-reviewed scholarly journals, ignoring gray literature that might be published by practitioners in the field (Garousi, Felderer & Mäntylä, 2019). Future literature reviews might adopt a design to avoid such limitations. Also, considering the problem with how loosely and generically ST is defined in existing literature, it is recommended that future studies carefully acknowledge the influence of content and context of ST as mediating variables, and consider exploring precise measures of ST such as passive viewing ST, gaming ST, socio-recreational ST, and educational ST. Also, since there is a dearth of literature on educational ST, it is suggested that more empirical studies be carried

Annexure A
Checklist for assessing the quality of quantitative studies from Kmet et al. (2004).

	Criteria	Yes (2)	Partial (1)	No (0)	N/A
1	Question / objective sufficiently described?				
2	Study design evident and appropriate?				
3	Method of subject/comparison group selection or source of information/input variables described and appropriate?				
4	Subject (and comparison group, if applicable) characteristics sufficiently described?				
5	If interventional and random allocation was possible, was it described?				
6	If interventional and blinding of investigators was possible, was it reported?				
7	If interventional and blinding of subjects was possible, was it reported?				
8	Outcome and (if applicable) exposure measure(s) well defined and robust to measurement / misclassification bias? Means of assessment reported?				
9	Sample size appropriate?				
10	Analytic methods described/justified and appropriate?				
11	Some estimate of variance is reported for the main results?				
12	Controlled for confounding?				
13	Results reported in sufficient detail?				
14	Conclusions supported by the results				

out to assess the associations between educational ST and educational, physiological and psychological outcomes for users with both - typical and special needs. Further, we encourage studies to report their results in either regression coefficients or correlation coefficients so that they can be transformed to standardized measures without much error for the use of meta-studies. Additionally, it is suggested that researchers consider using more objective measures of ST instead of the typically used self-report instrumentation whose validity and reliability is often questioned.

Finally, and most importantly, we recommend that studies should carefully interpret the significance of their findings - more specifically, the magnitude of the effect sizes in light of the large body of research methodology literature that is engaged in debate over the matter. Statistical significance reporting without contextually rooted interpretations of accompanying effect sizes can easily mislead well-intentioned policymakers, parents, and educators that do not have the competence to conduct critical analysis of the findings independently. And, as McCartney and Rosenthal (2000) expressed, we "need to be cognizant of the fact that real decisions for real children are influenced by the papers we write, regardless of whether we ever intended our papers to be used in the policy arena; for this reason, it is incumbent upon us to consider how others use our data." (p. 173).

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Availability of data and materials

Data used in this study have been attached as supplementary material.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ijedro.2021.100094.

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