Id: 1240475

Participatory Educational Research (PER)
Vol.10(3), pp. 226-246, May 2023
Available online at http://www.perjournal.com
ISSN: 2148-6123
http://dx.doi.org/10.17275/per.23.53.10.3

Development and Validation of a Screen Fatigue Scale

Gürbüz Ocak*
Department of Educational Sciences, Afyon Kocatepe University, Afyon, Turkey
ORCID: 0000-0001-8568-0364

Rüveysa Günhan
Ministry of Education, Konya, Turkey
ORCID: 0000-0002-8028-4378

Ahmet Murat Uzun
Department of Educational Sciences, Afyon Kocatepe University, Afyon, Turkey
ORCID: 0000-0002-1852-8802

Akın Karakuyu
Hatay Mustafa Kemal University, Hatay, Turkey
ORCID: 0000-0001-7370-5464

Article history
Received:
22.01.2023

Received in revised form:
01.03.2023

Accepted:
05.04.2023

Key words:
Screen fatigue; COVID-19, technology addiction; excessive screen use

Due to rapid development in information and communication technologies (ICT), daily life has been digitized with increasing momentum, and the COVID-19 pandemic has accelerated this situation more than ever. Depending on these developments and the excessive use of ICT, many new concepts have emerged, including screen fatigue. To this respect, this study aims to develop a scale that determines screen fatigue among adolescents caused by excessive screen use and test the scale's psychometric properties. The research was conducted with an exploratory sequential, mixed-method research design. In the study's first phase, qualitative data were obtained through a literature review and focus group interviews to develop an initial item pool. Based on the qualitative data analysis, a 56-item item pool was formed. In the quantitative phase, the item pool was administered to 365 students for the exploratory factor analyses (EFA). After determining the dimensions of the scale through EFA, it was administered to 417 students for confirmatory factor analysis (CFA). Quantitative data demonstrated that the scale has satisfactorily reliable and valid. A final scale was obtained, including 24 items and four factors named behavioral, physical, affective, and cognitive symptoms of screen fatigue.

* Correspondency: gocak@aku.edu.tr

Introduction

Information and communication technologies (ICT) have been a pervasive and indispensable part of our lives. A recent Digital Global Overview Report shows that global mobile phone and internet users have been rising, and the actual numbers might be even higher due to the COVID-19 pandemic (We Are Social, 2022). Another recent report published in Turkey has shown that access to and use of ICT has been on the rise over the last few years (TurkStat, 2021). Reports also have highlighted that ICT use is more prevalent among the younger population (Rideout et al., 2011; TurkStat, 2021).

Besides its benefits, such widespread dependency on technology carries some risks. Furthermore, more than ever, people come up against these risks during the pandemic because their lifestyle has changed dramatically due to self-quarantine, social distancing, lockdowns, and order to stay at home (Potas et al., 2022). During the pandemic, many people were forced to use ICT more frequently to fulfill their academic or work-related responsibilities, and thereby screen time increased (Ahorsu et al., 2022; Colomo Magaña et al., 2021; Potas et al., 2022; Saritepeci, 2021; Winther & Byrne, 2020). On the other side, excessive screen time may have some impact on a person's behavior, physical health, emotional stability, and cognitive health. (Liu et al., 2022).

Today, students are bombarded by different media and technologies such as televisions, tablets, smartphones, and computers (Saritepeci, 2021), consuming their time and energy. Students tend to switch between the screens of these devices and engage in multitasking behaviors (Cheever et al., 2018; Rosen et al., 2013). Furthermore, considering that the education was delivered through e-learning during the COVID-19 pandemic, one can assume that students' media exposure might have increased further. In other words, the more students interact with ICT devices, the more they risk encountering technology-related adverse outcomes. The literature emphasized that the pandemic aggravated learning losses (Akkaş Baysal & Ocak, 2021; Kaffenberger, 2021; UNESCO, 2020), technology or screen addiction (Gökalp et al., 2022), procrastination (Gökalp et al., 2022), psychological pressure (Cao et al., 2020) and COVID-19 fear (Ahorsu et al., 2022). However, research is scarce on diagnosing outcomes of excessive screen use with a well-developed psychological measure, although research concentrated on developing social media fatigue scale (Zhang et al., 2021). To that end, in this study, we aimed to develop a scale measuring the outcomes of excessive screen use. The scale was named "the screen fatigue."

Literature review

Excessive Screen Use

Recently, due to the proliferation of internet-enabled portable devices, people have had the opportunity to engage in digital activities without time and space limitations. These devices serve various purposes, making them useful during the day and night and even when traveling. These functions include entertainment features, mobility, accessibility, and connectivity (Balhara et al., 2018; Lin et al., 2020; Liu et al., 2022; Rosen et al., 2013).

Consequently, the issue of youngsters and teenagers using too much media has come to light (Liu et al., 2022).

In the literature, there is no consensus with respect to the definition and conceptualization of excessive screen use. One school of thought considers over-reliance on different media and technologies as "addiction." Accordingly, media addiction is seen as a behavioral addiction that does not involve using a chemical substance. Addictive media users, according to this definition, feel tempted to use media despite their adverse outcomes (LaRose et al., 2003). On the other hand, media overuse cannot always be regarded as an addiction. For example, Davis (2001) argued that people might use the internet for an amenable amount of time in a productive way. The important thing is not the duration of use but the extent to which media overuse replaces daily life responsibilities (Davis, 2001; Liu et al., 2022). In other words, "although excessive use may be a necessary condition for experiencing negative outcomes, it is not a sufficient condition" (Caplan & High, 2006, p. 267). Excessive use of the internet becomes problematic when individuals show a cognitive preoccupation with the media and use it compulsively (i.e., deficient self-regulation) (Caplan & High, 2006; Caplan, 2010).

The literature concentrated on ICT-mediated addictions, including internet, smartphone, social media, gaming, and internet gaming addiction, which are prevalent among adolescents (Gökalp et al., 2022; Zhang et al., 2021). However, it can be posited that each addiction type is likely to be limited to its respective media or technology. Therefore, in some studies, excessive use has been addressed under the term "screen addiction" to provide a more comprehensive and inclusive conceptualization (Gökalp et al., 2022; Lin et al., 2020; Saritepeci, 2021;). Furthermore, the literature did not reach a consensus on conceptualizing problematic media consumption. Various terms were used for dependence on using different media and technologies. These include unregulated internet use, internet addiction, internet dependence, problematic internet use, and smartphone addiction (Cheever et al., 2018; LaRose et al., 2003). Furthermore, although internet addiction was suggested to be involved in the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), it was eventually not considered a disorder except for internet gaming disorder (Cheever et al., 2018; Lozano-Blasco et al., 2022). Nevertheless, regardless of the definition and conceptualization of the phenomenon of addiction, it might be clear that adolescents consume time excessively or obsessively in front of the screen (Balhara et al., 2018; Saritepeci, 2021), and these might pose risks resulting in diverse adverse outcomes for individuals (Caplan, 2010; Liu et al., 2022; Zhang et al., 2021; Zheng & Lee, 2016). Given the literature, the current study did not simply consider the overuse of media and technology as "addiction" or "problematic." Furthermore, instead, it focused on the outcomes of spending excessive time in front of the screens. Next, the literature on the negative consequences of excessive screen use was reviewed.

Adverse outcomes related to excessive screen usage.

Although a plethora of evidence suggests that the media is essential for the development of young people, studies also indicated that media consumption results in many unfavorable health outcomes, such as violence, obesity, and tobacco use (Rideout et al., 2011). Excessive screen use is regarded as a health concern showing a dose-response link associated with many health risks among adults (Sigman, 2014). The research reflects that every hour of screen exposure might worsen the symptoms (Caplan & High, 2006; Sigman, 2014).

According to the cognitive-behavioral theory of generalized problematic Internet use (GPIU), cognitive and behavioral symptoms are two salient symptoms associated with the GPIU (Caplan, 2010; Davis, 2001; Zheng & Lee, 2016). Liu et al. (2022) reviewed the studies on screen overuse and associated outcomes. It was found that screen overuse is related to individuals' physical, cognitive, emotional, and behavioral well-being. Zheng and Lee (2016) explored the excessive use of social media. They found excessive use is related to mental preoccupation, which conflicts with family, personal, and work responsibilities. Zhang et al. (2021) developed a scale measuring social media fatigue with multi-dimensions involving cognitive, behavioral, and emotional aspects. Saritepeci (2021) developed a multiscreen addiction scale. According to the scale, loss of control and compulsive behavior are the two most important factors explaining multiple-screen addiction. Karadağ and Kiliç (2019) investigated Turkish students' technology addiction based on their teachers' views. Technology addiction was found to interfere with students' physical, social, and psychological lives. Uzun and Kilis (2019) explored university students' use of different media and technology and found that the more students are involved with media, the lower their academic achievement.

Screen exposure might become more problematic alongside the pandemic because students had to stay home due to the lockdown prohibitions. During the pandemic, students benefited from digital media to participate in leisure and social activities. Furthermore, they received online education, which might have aggravated their exposure to screen media (Guo et al., 2021). Özdemir and Arpacıoğlu (2020) showed that 60% of the adult participants expanded their use of social media during the pandemic. Moreover, they reported that 35% of the students spent four or more time on social media. Duan et al. (2020) also demonstrated that Chinese students' time devoted to the internet increased during the pandemic indicating that 29.58% of students' screen time was more than 5 hours a day. Lemenager et al.(2021) found plenty of participants (71.4%) reported growing media consumption usage and consequent screen time during the lockdown in Germany.

Research demonstrated that school closures during the pandemic dramatically negatively impacted students' health outcomes featuring a decline in physical activity, a rise in screen time, and irregular sleeping (Guo et al., 2021). Serra et al. (2021) surveyed 184 school-aged Italian students to determine the outcomes of excessive smartphone use during the pandemic. It was found that students exhibited growing smartphone usage during the pandemic leading to some adverse clinical, psychological, and social outcomes. A study conducted in Spain demonstrated that children and adolescents showed deteriorating health behaviors involving decreased physical activity, greater use of the screen, and a decline in fruit and vegetable intake on a daily basis (López-Bueno et al., 2020).

The current study

Previous research on problematic media consumption concentrated on various types of behavioral addiction, including internet, smartphone, social media, gaming, or internet gaming addiction (Gökalp et al., 2022). However, one might argue that individuals' media exposure has increased recently due to the proliferation of different technological devices, either portable or stable. Regardless of the medium or platform names, adolescents spend time in front of the screen excessively, which might have been exacerbated during the COVID-19 pandemic (Saritepeci, 2021). When the literature is examined, it can be found that excessive screen use is related to many behavioral, psychical, cognitive, and emotional outcomes (Liu et al., 2022; Neophytou et al., 2021). However, there is a scarcity of research concentrating on measuring a scale on the outcomes of excessive screen use. As Zheng and Lee (2016) discussed, some studies have employed a cognitive-behavioral paradigm to investigate problematic internet consumption (Caplan, 2010). Although research concentrated on developing a scale for "social media fatigue" (Zhang et al., 2021), there is still a need to develop approaches to measure outcomes associated with excessive screen use.

Furthermore, as indicated by Zheng and Lee (2016), in the generalized problematic internet use framework, three items were used to measure negative outcomes (Caplan, 2010). Since students reported many health problems due to excessive use during the pandemic (Demir & Yildizli, 2022), it could be a reasonable approach to develop a measurement tool for outcomes of excessive screen use (i.e., screen fatigue). Given this rationale, this study aims to construct a screen fatigue scale to measure the outcomes of excessive screen use. The scale is intended to contribute theory of excessive media consumption by considering the outcomes of excessive screen use more inclusively. Practitioners can also use the scale to help people use the ICT more functionally.

Methodology

In the present study A mixed-method design in which qualitative and quantitative data were collected was employed. The exploratory sequential design was employed, as the qualitative data were collected and analyzed first, and then the quantitative data (Creswell & Plano Clark, 2018).

Research procedure and participants

In the study, first, the literature was reviewed to develop an interview form regarding screen fatigue. Then, a semi-structured interview form was created, including seven open-ended questions. The interview form involved questions regarding the duration, purpose, and effect of excessive media consumption during the COVID-19 pandemic. For example, students were asked the following questions to understand their purpose for and duration of using digital media: "For what purposes do you stand in front of digital screens? (For what purposes do you use TV, tablet, phone, computer?) and "on average, how long do you stay in front of the screen during the day?". The following questions were used to understand the effect of being overexposed to different screens: (a) how do you feel towards the end of the day when you spend too much time in front of the screen, (b) If you are tired of staying in front of the screen for a long time; what/what would you like to do? What/what would you not like to do? For collecting qualitative data, a semi-structured interview form was employed. Qualitative data were obtained from 14 students with a focus group interview. Content analysis was used to analyze qualitative data. As a result of the qualitative data analysis, an item pool's initial form (56 items) was created.

As a next step, two field experts, two psychology experts, and one language expert evaluated the scale with respect to content and face validity. After that, the scale was piloted on ten high school students participating voluntarily in the study to check the items' clarity and understandability. The scale was revised based on feedback from the students and experts. Accordingly, the final form of the item pool was prepared.

In the study's quantitative phase, the final form of the item pool was administrated. The items were rated on a Likert-type scale (5 points) ranging from completely disagree [1], to completely agree [5]. The total score obtained from the scale indicates more vulnerability to screen fatigue.

For the exploratory factor analyses (EFA), the scale was applied to 365 high school students. Two respondents' data were dropped because their responses were given the same ratings for all questions. In total, 363 students' data were analyzed. For the confirmatory factor analysis (CFA), a separate study was performed with a different group of 417 students. The scale was finalized after calculating the reliability and validity values. The research procedure is illustrated in the following figure:

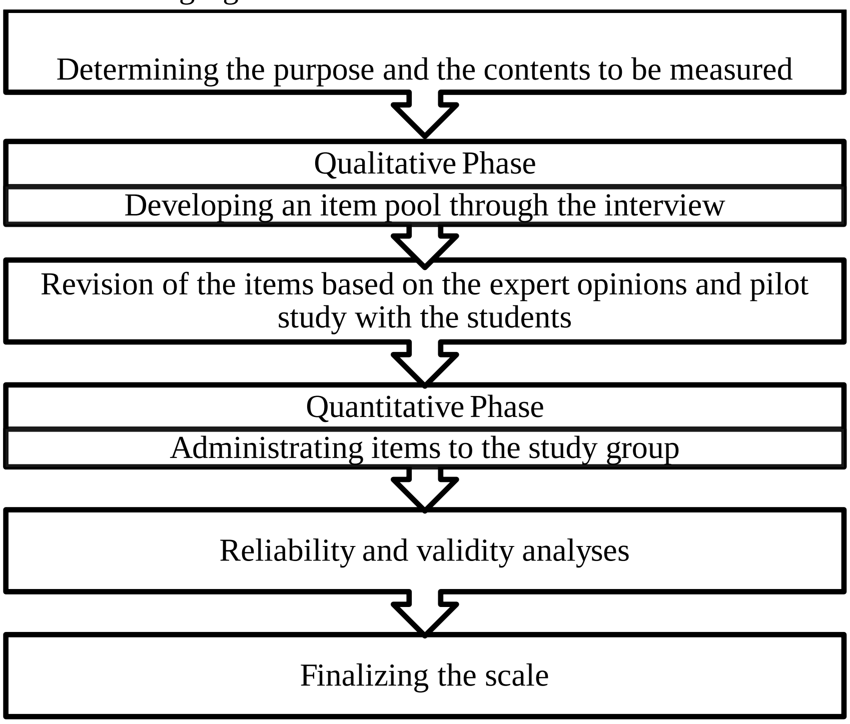

Figure 1. Research procedure

Results

In the first phase, three experts analyzed the qualitative data through content analyses. The reliability of the qualitative data was tested with the opinion agreement formula suggested by Miles and Huberman (1994). According to Patton (2002), the consensus coefficient value should be at least 80%. The following formula calculates reliability: "(Consensus / Disagreement + Consensus) *100." Reliability was found as 82.4%. Five key concepts emerged based on the content analyses of the qualitative data and the reviewed literature. These key concepts were *psychological, behavioral, physical, affective, and cognitive symptoms* related to screen fatigue. However, after an in-depth second analysis, it was realized that the students' responses regarding the key concepts of psychological and affective symptoms overlapped. Furthermore, expert opinions suggested that psychological symptoms and affective symptoms can be merged into one category, which is determined as "affective symptoms." In Table 1, the key concepts found obtained through qualitative analyses are explained in detail.

Table 1. Key concepts found in the qualitative analyses

Concepts	**Description**	**Symptoms**
Behavioral Symptoms	Effects of screen fatigue on the behavior of the individual.	Going out for fresh air, Resting eyes
Physical Symptoms	Effects of screen fatigue on the body of the individual	Red eyes, neck and back pains
Affective Symptoms	Effects of screen fatigue on the emotion of the individual	Not enjoying playing game as before, becoming nervous when the time spent in front of the screen is too much
Cognitive Symptoms	Effects of screen fatigue on the cognition of the individual	Decreased perception, forgetting stuff quickly when the time spent in front of the screen is too much

As a next step, quantitative data were analyzed in order to validate the key concepts found in the qualitative part. Firstly, EFA was employed in this study because it was important to reveal the factors' structure and their respective items rather than testing a particular hypothesis.

Before conducting factor analysis, first, it was assessed whether the data was suitable for EFA. Firstly, the normality of the data was tested, and it was shown that the data were distributed normally. Secondly, it was demonstrated that the dataset met the sample size requirement ($N > 300$) (Pallant, 2016). Thirdly, the dataset was furtherly tested for sampling adequacy through the Kaiser-Meyer-Olkin (KMO) statistics, which should be at least .60 for good factor analysis (Tabachnick & Fidell, 2007). As Table 2 shows, the KMO value was greater than the recommended value for the first and last step of the analyses. Finally, Bartlett's Test of Sphericity (BTS) was used to control whether the correlation matrix is equal to the identity matrix. The chi-Square value was significant ($p <.000$), which supported that the correlation matrix is not equal to the identity matrix, meaning that the dataset was found to be appropriate for factor analyses.

Table 2. Initial and final analysis

Initial Analysis			Final Analysis		
KMO Value		.954	KMO Value		.935
Barlett Test's of Sphericity	Approx. Chi-Square	14611.880	Barlett Test's of Sphericity	Approx. Chi-Square	5120.190
	Df	1540		Df	276
	Sigma	.000		Sigma	.000

After assumption testing, the main analyses of the EFA were conducted. The initial factor analysis yielded nine factors explaining 65.4 % of the total variance. However, based on the findings obtained in the qualitative part and the results of the scree plot (Figure 2), EFA was reconducted again with four fixed factors.

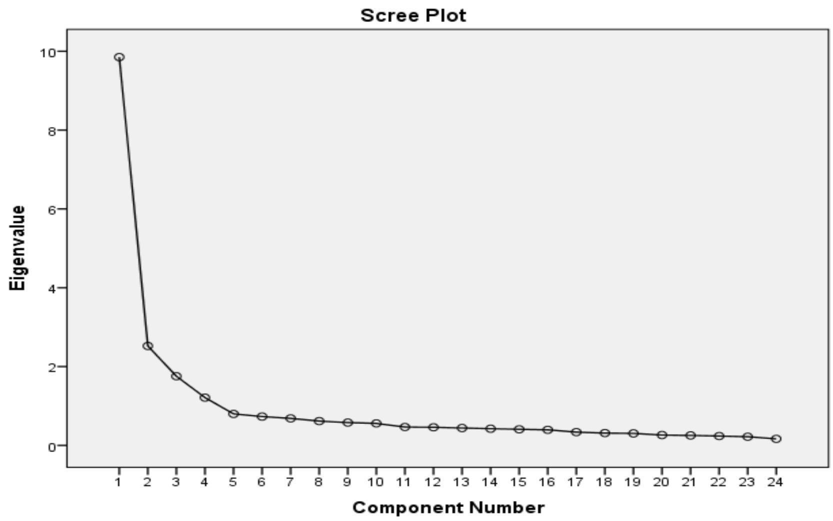

Figure 2. Scree Plot

Since the purpose of the analysis is data reduction, the varimax rotation method, one of the rotation methods, was used. "The most commonly used orthogonal approach is the Varimax method, which attempts to minimize the number of variables that have high loadings on each factor" (Pallant, 2016, p. 186). After the rotations process, the screen fatigue scale was formed with 24 items and four sub-dimensions. These sub-dimensions were consistent with those obtained from the literature and also generated from the qualitative analysis. Factor 1 was interpreted as physical symptoms sub-dimension and accounted for 21 % variance. Factor 2 was interpreted as a cognitive symptoms sub-dimension and explained 15 % of the variance. Factor 3 was interpreted as behavioral symptoms sub-dimension and contributed to 14% of the variance. Finally, factor 4 was interpreted as affective symptoms sub-dimension and contributed to 12 % of the total variance. The total variance of the scale is 63.9%. As a general rule, this should be at least 50% (Streiner, 1994). The variance table is given in Table 3.

Table 3. Total variance explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	9.852	41.049	41.049	9.852	41.049	41.049	5.097	21.237	21.237
2	2.523	10.512	51.561	2.523	10.512	51.561	3.695	15.397	36.635
3	1.755	7.313	58.874	1.755	7.313	58.874	3.453	14.386	51.020
4	1.213	5.052	63.926	1.213	5.052	63.926	3.097	12.906	63.926
5	.799	3.330	67.257						
6	.732	3.049	70.305						
7	.685	2.856	73.161						
8	.617	2.570	75.731						
9	.579	2.411	78.141						
10	.558	2.325	80.467						
11	.467	1.947	82.414						
12	.459	1.911	84.325						
13	.441	1.837	86.161						
14	.424	1.768	87.929						
15	.408	1.702	89.631						
16	.395	1.646	91.277						
17	.337	1.405	92.683						
18	.313	1.306	93.989						
19	.304	1.266	95.255						
20	.263	1.097	96.352						
21	.253	1.053	97.405						
22	.237	.986	98.390						
23	.220	.915	99.306						
24	.167	.694	100.000						

Table 4. Rotated component matrix

Items	Component			
	1	2	3	4
M8	.745			
M6	.742			
M11	.735			
M10	.723			
M9	.691			
M7	.688			
M1	.672			
M3	.544			
M15	.498			
M23		.802		
M22		.800		
M21		.779		
M20		.764		
M25		.711		
M55			.795	
M54			.784	
M56			.775	
M41			.701	
M42			.571	
M50			.522	
M38				.834
M39				.801
M37				.800
M36				.653

According to Table 4, the first factor included nine items due to the rotation process, the second factor had five items, and the third one included six items. Finally, the fourth factor involved four items. This research determined the cut-off point for an item as .40 (Stevens, 2002), and items with a factor load below this value were excluded. Additionally, if items loaded highly on two factors and the difference between these values was lower than .10, these items were also deleted. Factor load values for 24 items ranged from .498 and .834. Since there are only four items with a load value below 0.60, it can be deduced that generally, the scale's load values are high.

As a next step, the reliability of the whole scale and as well as the subscales were calculated. The reliability of the whole scale was found to be .936, which is quite sufficient. Additionally, the reliability values of the sub-scales were satisfactorily high with .901 for the physical symptoms sub-dimension, .906 for the cognitive symptoms sub-dimension, .880 for the affective symptoms sub-dimension, and .843 for the behavioral symptoms sub-dimension, respectively. Considering that the scale was applied once, internal consistency was also calculated using the Split-half split method. The Spearman-Brown technique is built on the premise that the half-tests are parallel, and so the split-half score variances are equivalent (Cho & Kim, 2015). In the current study, the scale was divided into two parts randomly. Cronbach alpha value was found to be .914 for part 1 and .883 for part 2, which means the alpha coefficients of these two groups were close to each other. In addition, this can be corroborated by the positive, strong correlation found between the two groups (*r*: .707). Furthermore, Spearman-Brown Coefficient was found as .828, which is quite satisfactory. Given the results above, it can be inferred that the scale is sufficiently reliable. After reliability, the correlations among constructs were calculated and given in Table 5.

Table 5. Correlation among factors

Factors	N	1.	2.	3.	4.
1. Physical	363	-	-	-	-
2. Cognitive	363	.656	-	-	-
3. Behavioral	363	.523	.331	-	-
4. Affective	363	.536	.519	.512	-

As EFA corroborated the qualitative results, as a next step, confirmatory factor analysis (CFA) was conducted to validate the scale's factorial structure having 24 items and four constructs. CFA was conducted with 417 students having similar characteristics to those who participated in the EFA. Both first-order and second-order factor analyses of CFA were conducted. When the t values were examined, it was observed that all items significantly loaded onto their respective factors. Additionally, none of the items had a factor loading value below .40 (Stevens, 2002). A path diagram related to the first-order CFA was given in Figure 2.

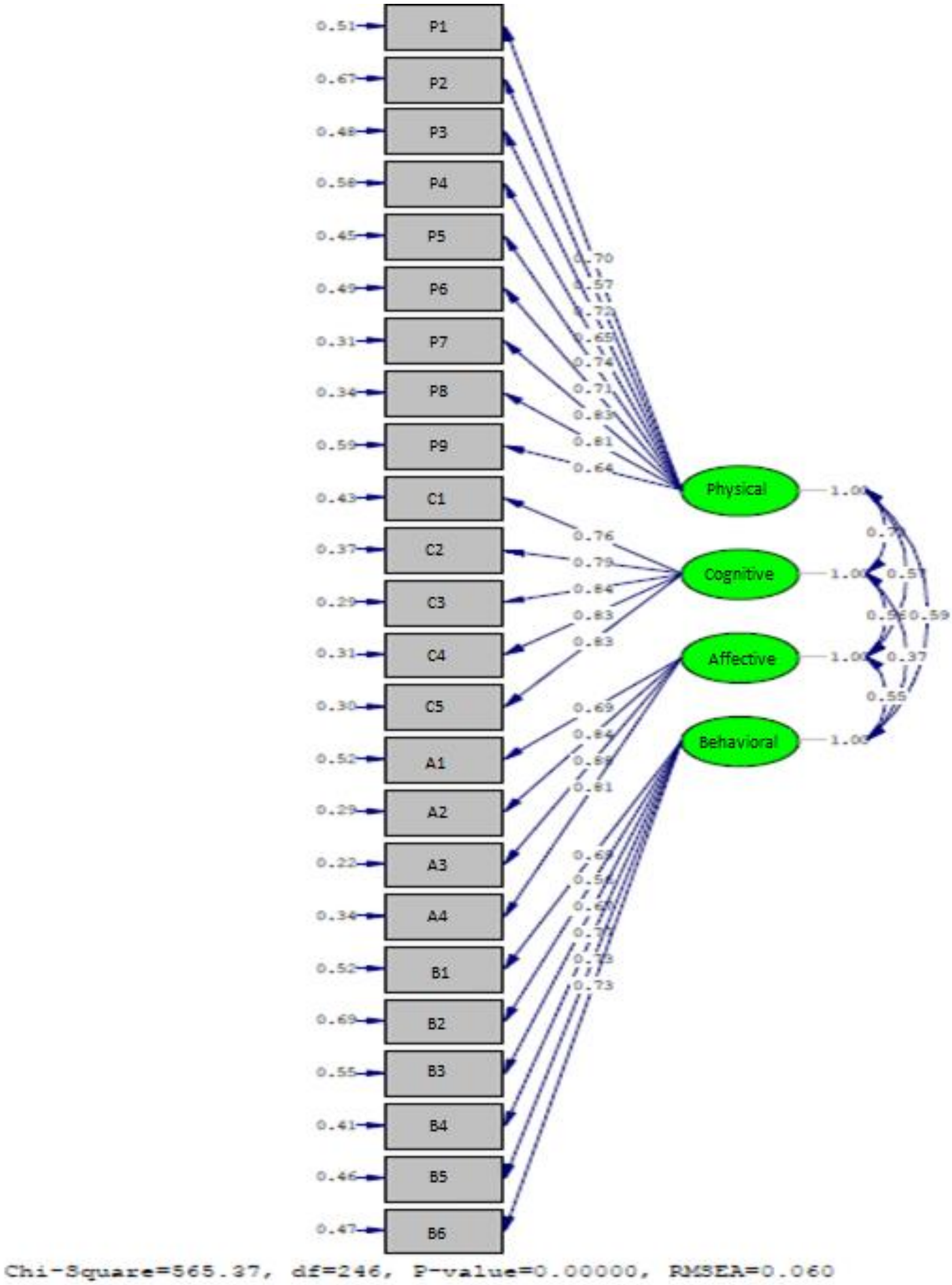

Figure 3. Path diagram of the first order CFA

A second-order CFA was conducted after the first-order CFA to determine whether the whole scale measures screen fatigue unidimensionally. In this step, four first-order factors (Physical, Cognitive, Affective, and Behavioral Symptoms) were loaded onto the second-order factor of screen fatigue. A path diagram related to the second-order CFA is given in Figure 3:

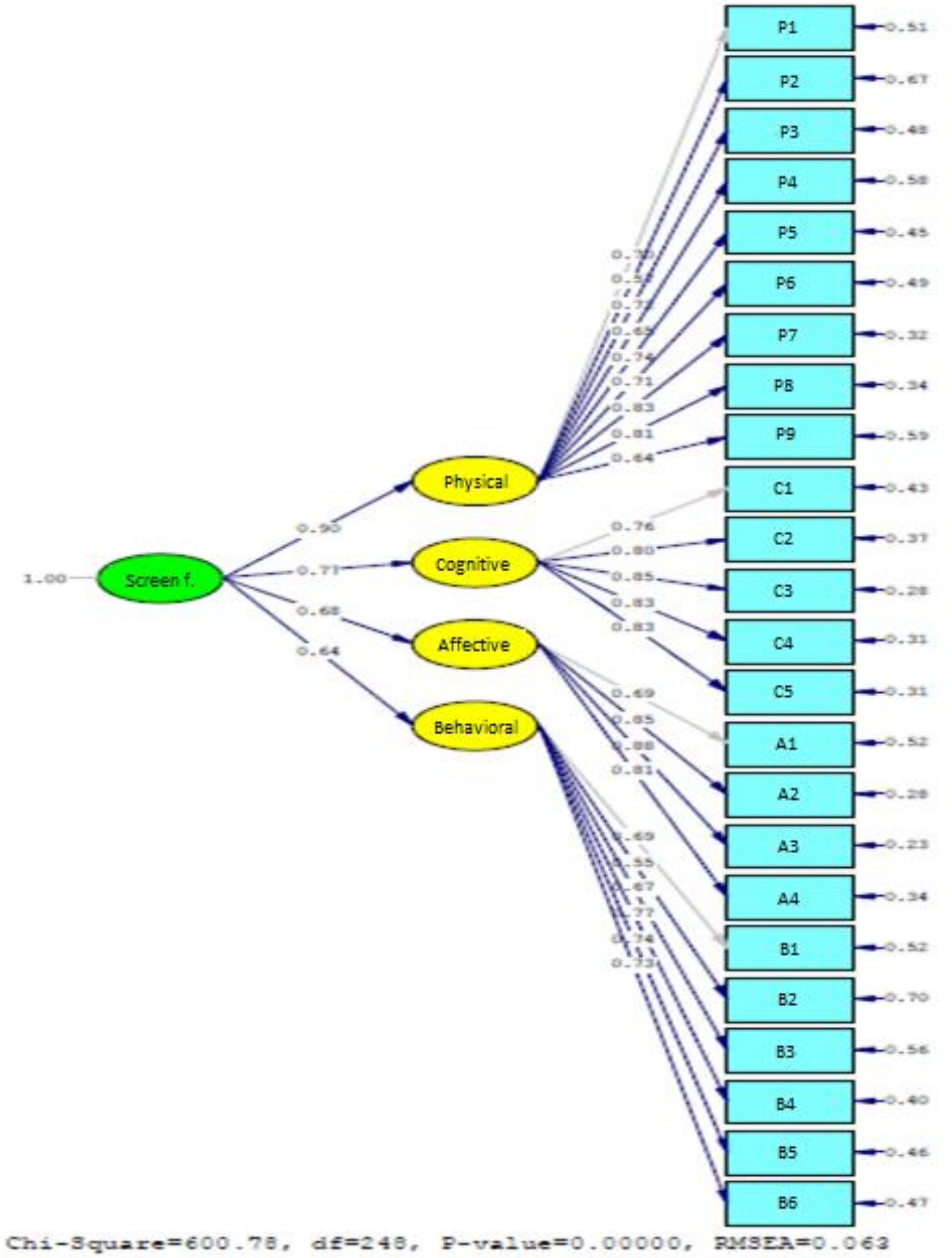

Figure 4. Path diagram of the second-order CFA

Table 6 CFA fit values (Hu & Bentler, 1999; Meyers et al., 2017)

Fit criteria	Perfect Fit	Acceptable Fit	Results obtained from the scale
X^2/ df	$0 \leq x^2/df \leq 3$	$x^2/df \leq 5$	x^2/df =2.42
RMSEA	0 ≤ RMSEA≤ .05	RMSEA≤ .08	RMSEA= .063
NNFI	≥ .95	≥ .90	.98
AGFI	≥ .95	≥ .90	.83
GFI	≥ .95	≥ .90	.90
CFI	≥ .95	≥ .90	.98
NFI	≥ .95	≥ .90	.96
RFI	≥ .95	≥ .90	.96
IFI	≥ .95	≥ .90	.98
SRMR	≤ .05	≤ .10	.05
PNFI	≥ .95	≥ .50	.86
PGFI	≥ .95	≥ .50	.73

According to Figure 3 and Table 6, results obtained by the second-order CFA proposed a good fit: Chi-Square/df = 2.42, RMSEA = 0.063, CFI = 0.98, SRMR = 0.05. Regression coefficients between the second-order factor (screen fatigue) and three first order factors were 0.90, 0.73, 0.68, and 0.64 for physical, cognitive, affective, and behavioral symptoms, respectively. These values were close to the .70 benchmark value suggested by Chin 1998. Based on the second-order CFA, screen fatigue scale can be used as a unitary scale.

Discussion and Conclusion

This study aimed to develop a scale to determine the screen fatigue of individuals, which is reliable and valid. In the literature review conducted before the scale development, it was found that there were not enough studies on the concept of screen fatigue to the best of our knowledge. Moreover, a measurement tool for screen fatigue was not found. In this sense, the screen fatigue scale, which was found to be satisfactorily valid and reliable, is planned to contribute to the field theoretically and practically. Theoretically, it can expand the knowledge base on problematic media consumption by focusing on the outcomes associated with the issue. Practically, it can be used to determine the consequences of consuming excessive amounts of time in front of the screen.

The current study was conducted through exploratory sequential design. Qualitative data were collected through a literature review and focus group interviews, and an item pool of 56 items was created by analyzing these data. After exploratory factor analyses with varimax rotation, items below the threshold value or loaded on more than one factor were omitted from the analyses. Finally, the remaining 24 items loaded on four factors, which were conceptualized as physical, cognitive, affective, and behavioral symptoms of screen fatigue. Construct validity was tested through confirmatory factor analysis (CFA). Results showed that $x2/df$ was found as 2.42, indicating a perfect fit, and RMSEA value was 0.063 indicating an acceptable fit. Results also showed that other fit values fall in either acceptable or perfect fit as well.

During the COVID-19 lockdown, people tended to spend excessive time in front of the screen

(Saritepeci, 2021) to satisfy their social, academic, work, and recreational needs. In other words, screens were the only medium to sustain life. However, excessive screen consumption also brought some outcomes with it. In this study, the outcomes of excessive screen use were conceptualized as screen fatigue. Regarding how excessive use resulted in screen fatigue, one of the students in the focus group discussion stated their view as follows:

> I used to run away from school and go to the internet cafe to play computer, but now I have time, I have the opportunity to play at home, but I don't want to do these things like I used to. They get boring. I don't even want to text anyone or attend classes anymore.

According to Peper and Harvey (2021), screen fatigue and excessive use of technology are a syndrome. One of the ways to prevent it is to reduce screen addiction. Koayess and McCaw (2020) mentioned that screen fatigue has emerged as a problem in online education. Educators should support innovative and creative learning by taking students' autonomy a little further away from the screen to overcome this problem.

Excessive and careless use of digital technologies might create fatigue, preventing healthy use of the technology. This situation might disrupt the bodily integrity of individuals both physically and mentally. Problematic internet and technology use can cause psychological disorders such as depression, loneliness, and high level of anxiety in individuals (Fernandes, et al., 2020; Chen, et al., 2020), physical disorders such as the low back, head and back pain, wrist and finger pain, burning in the eyes and eye disorders (Borhany et al., 2018; Janwantanakul et al., 2009; Rosenfield, 2016). The screen fatigue scale can be used to determine how serious excessive screen use is by measuring physical, cognitive, affective, and behavioral symptoms associated with screen fatigue.

Healthy technology usage appears as a skill that should be acquired from childhood. With the developed screen fatigue scale, parents will be able to take measures to ensure the beneficial use of technology and prevent technology addiction by being aware of the screen fatigue level of their children. The psychological program (Berdibaeva, et al., 2016) and the youth program (Shek, et al., 2016) developed to prevent excessive use of technology were found to be effective in reducing students' technology addiction. In such programs, the screen fatigue scale of which validity and reliability were ensured, can be used by psychological counselors and academics as a data collection tool. Teachers can also benefit from the scale to gauge whether screen fatigue is associated with academic achievement.

As a result, a practical, valid and reliable scale consisting of 24 items and four factors with high reliability (α:0.936) was developed to determine the screen fatigue of students. As the total score indicates more screen fatigue. The lowest score obtained from the scale is 24, while the highest score is 120.

The study has some limitations. First of all, the study's results are limited to those students' responses who participated in the study. This study can be replicated with different cultures to examine its cultural validity. Second, similar to Saritepeci (2021), this study was conducted during the COVID-19 pandemic. Therefore, students might have overestimated their screen use, or their usual screen consumption might be slightly different than during COVID-19. Third, social desirability bias might occur in studies where questionaries are used involving sensitive measures. The researchers tried their best to preserve students' anonymity and confidentiality. Nevertheless, students might have responded to the items in a socially desirable way. Future studies can control social desirability bias to obtain more reliable data.

References

Ahorsu, D. K., Lin, C.-Y., Imani, V., Saffari, M., Griffiths, M. D., & Pakpour, A. H. (2022). The fear of COVID-19 scale: Development and initial validation. *International Journal of Mental Health and Addiction*, *20*(3), 1537–1545. https://doi.org/10.1007/s11469-020-00270-8

Akkaş Baysal, E., & Ocak, G. (2021). Opinions of the teachers on the compensation of learning loss caused by the COVID-19 outbreak. *Kastamonu Education Journal*, *29*(4), 173-184. https://doi.org/10.24106/kefdergi.811834

Al-Furaih, S. A. A., & Al-Awidi, H. M. (2020). Teachers' change readiness for the adoption of smartphone technology: personal concerns and technological competency. *Technology, Knowledge and Learning*, *25*(2), 409-432. https://doi.org/10.1007/s10758-018-9396-6

Balhara, Y. P. S., Verma, K., & Bhargava, R. (2018). Screen time and screen addiction: Beyond gaming, social media and pornography– A case report. *Asian Journal of Psychiatry*, *35*, 77-78. https://doi.org/10.1016/j.ajp.2018.05.020

Berdibayeva, S., Garber, A., Ivanov, D., Massalimova, A., Kukubayeva, A., & Berdibayev, S. (2016). Psychological prevention of older adolescents' interpersonal relationships, who are prone to internet addiction. *Procedia - Social and Behavioral Sciences*, *217,* 984–989. https://doi.org/10.1016/j.sbspro.2016.02.081

Borhany, T., Shahid, E., Siddique, W. A., & Ali, H. (2018). Musculoskeletal problems in frequent computer and Internet users. *Journal of Family Medicine and Primary Care*, *7*(2), 337–339. https://doi.org/10.4103/jfmpc.jfmpc_326_17

Cao, W., Fang, Z., Hou, G., Han, M., Xu, X., Dong, J., & Zheng, J. (2020). The psychological impact of the COVID-19 epidemic on college students in China. *Psychiatry Research*, *287*, 112934. https://doi.org/10.1016/j.psychres.2020.112934

Caplan, S. E., & High, A. C. (2006). Beyond excessive use: The interaction between cognitive and behavioral symptoms of problematic internet use. *Communication Research Reports*, *23*(4), 265-271. https://doi.org/10.1080/08824090600962516

Caplan, S. E. (2010). Theory and measurement of generalized problematic Internet use: A two-step approach. *Computers in Human Behavior*, *26*(5), 1089-1097. https://doi.org/10.1016/j.chb.2010.03.012

Cheever, N. A., Moreno, M. A., & Rosen, L. D. (2018). When does internet and smartphone use become a problem? In M. A. Moreno & A. Radovic (Ed.), *Technology and Adolescent Mental Health* (ss. 121-131). Springer International Publishing. https://doi.org/10.1007/978-3-319-69638-6_10

Chen, R. N., Liang, S. W., Peng, Y., Li, X. G., Chen, J. B., Tang, S. Y. ve Zhao, J. B. (2020). Mental health status and change in living rhythms among college students in China during the COVID-19 pandemic: A large-scale survey. *Journal of Psychosomatic Research*, *137*, 110219. https://doi.org/10.1016/j.jpsychores.2020.110219

Chin, W. W. (1998). Commentary: Issues and opinion on structural equation modeling. *MIS Quarterly*, *22*(1), vii-xvi.

Cho, E., & Kim, S. (2015). Cronbach's coefficient alpha: Well known but poorly understood. *Organizational Research Methods*, *18*(2), 207-230. https://doi.org/10.1177/1094428114555994

Colomo Magaña, E., Cívico Ariza, A., Ruiz Palmero, J., & Sánchez Rivas, E. (2021). Problematic use of ICTs in trainee teachers during COVID-19: A sex-based analysis. *Contemporary Educational Technology*, *13*(4). https://eric.ed.gov/?id=EJ1316731

Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research* (Third edition). SAGE.

Davis, R. A. (2001). A cognitive-behavioral model of pathological Internet use. *Computers in Human Behavior*, *17*(2), 187-195. https://doi.org/10.1016/S0747-5632(00)00041-8

Demir, M. R., & Yildizli, H. (2022). Educational processes and learning at home during COVID-19: Parents' experiences with distance education. *International Review of Research in Open and Distributed Learning*, *23*(3), 1–20. https://doi.org/10.19173/irrodl.v23i2.5870

Duan, L., Shao, X., Wang, Y., Huang, Y., Miao, J., Yang, X., & Zhu, G. (2020). An investigation of mental health status of children and adolescents in china during the outbreak of COVID-19. *Journal of Affective Disorders*, *275*, 112-118. https://doi.org/10.1016/j.jad.2020.06.029

Fernandes, B., Biswas, U. N., Mansukhani, R. T., Casarín, A. V., & Essau, C. A. (2020). The impact of COVID-19 lockdown on internet use and escapism in adolescents. *Revista de Psicología Clínica Con Niños y Adolescentes*, *7*(3), 59–65.

Gökalp, Z. Ş., Saritepeci, M., & Durak, H. Y. (2022). The relationship between self-control and procrastination among adolescent: The mediating role of multi screen addiction. *Current Psychology*. https://doi.org/10.1007/s12144-021-02472-2

Guo, Y., Liao, M., Cai, W., Yu, X., Li, S., Ke, X., Tan, S., Luo, Z., Cui, Y., Wang, Q., Gao, X., Liu, J., Liu, Y., Zhu, S., & Zeng, F. (2021). Physical activity, screen exposure and sleep among students during the pandemic of COVID-19. *Scientific Reports*, *11*(1), 8529. https://doi.org/10.1038/s41598-021-88071-4

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Janwantanakul, P., Pensri, P., Jiamjarasrangsi, W., & Sinsongsook, J. (2009). Associations between prevalence of self-reported musculoskeletal symptoms of the spine and biosychosocial factors among office workers, *Journal of Occupational Health*, *51*, 114-122.

Kaffenberger, M. (2021). Modelling the long-run learning impact of the Covid-19 learning shock: Actions to (more than) mitigate loss. *International Journal of Educational Development*, *81*, 102326. https://doi.org/10.1016/j.ijedudev.2020.102326

Karadağ, E., & Kiliç, B. (2019). Technology addiction among students according to teacher views. *Current Approaches in Psychiatry*, *11*, 101-117. https://doi.org/10.18863/pgy.556689

Khan, M. A. (2021). COVID-19's impact on higher education: A rapid review of early reactive literature. *Education Sciences*, *11*(8), 421. https://doi.org/10.3390/educsci11080421

Király, O., Potenza, M. N., Stein, D. J., King, D. L., Hodgins, D. C., Saunders, J. B., Griffiths, M. D., Gjoneska, B., Billieux, J., Brand, M., Abbott, M. W., Chamberlain, S. R., Corazza, O., Burkauskas, J., Sales, C. M. D., Montag, C., Lochner, C., Grünblatt, E., Wegmann, E., … Demetrovics, Z. (2020). Preventing problematic internet use during the COVID-19 pandemic: Consensus guidance. *Comprehensive Psychiatry*, *100*, 152180. https://doi.org/10.1016/j.comppsych.2020.152180

Koayess, P., & McCaw, T. (2020). Mitigating screen fatigue in virtual learning. *ICERI2020 Proceedings*, 4979–4979. https://doi.org/10.21125/iceri.2020.1079

Kuhfeld, M., Soland, J., Tarasawa, B., Johnson, A., Ruzek, E., & Liu, J. (2020). Projecting the potential impact of COVID-19 school closures on academic achievement. *Educational Researcher*, *49*(8), 549-565. https://doi.org/10.3102/0013189X20965918

Kuhfeld, M., & Tarasawa, B. (2020). *The COVID-19 slide: What summer learning loss can tell us about the potential impact of school closures on student academic achievement*. https://www.nwea.org/content/uploads/2020/05/Collaborative-Brief_Covid19-Slide-APR20.pdf

LaRose, R., Lin, C. A., & Eastin, M. S. (2003). Unregulated internet usage: Addiction, habit, or deficient self-regulation? *Media Psychology*, *5*(3), 225-253. https://doi.org/10.1207/S1532785XMEP0503_01

Lee, A. (2020). Wuhan novel coronavirus (COVID-19): Why global control is challenging? *Public Health*, *179*, A1-A2. https://doi.org/10.1016/j.puhe.2020.02.001

Lemenager, T., Neissner, M., Koopmann, A., Reinhard, I., Georgiadou, E., Müller, A., Kiefer, F., & Hillemacher, T. (2021). COVID-19 Lockdown restrictions and online media consumption in Germany. *International Journal of Environmental Research and Public Health*, *18*(1), 14. https://doi.org/10.3390/ijerph18010014

Lin, T. T. C., Kononova, A., & Chiang, Y.-H. (2020). Screen addiction and media multitasking among American and Taiwanese users. *Journal of Computer Information Systems*, *60*(6), 583-592. https://doi.org/10.1080/08874417.2018.1556133

Liu, J., Li, B., Sun, Y., Chen, Q., & Dang, J. (2021). Adolescent vision health during the outbreak of COVID-19: Association between digital screen use and myopia progression. *Frontiers in Pediatrics*, *9*. https://www.frontiersin.org/articles/10.3389/fped.2021.662984

Liu, J., Riesch, S., Tien, J., Lipman, T., Pinto-Martin, J., & O'Sullivan, A. (2022). Screen media overuse and associated physical, cognitive, and emotional/behavioral outcomes in children and adolescents: an integrative review. *Journal of Pediatric Health Care*, *36*(2), 99-109. https://doi.org/10.1016/j.pedhc.2021.06.003

López-Bueno, R., López-Sánchez, G. F., Casajús, J., Calatayud, J., Gil-Salmerón, A., Grabovac, I., Tully, M., & Smith, L. (2020). Health-related behaviors among school-aged children and adolescents during the Spanish COVID-19 confinement. *Frontiers in Pediatrics*, *8*. https://www.frontiersin.org/article/10.3389/fped.2020.00573

Lozano-Blasco, R., Latorre-Martínez, M., & Cortés-Pascual, A. (2022). Screen addicts: A meta-analysis of internet addiction in adolescence. *Children and Youth Services Review*, *135*, 106373. https://doi.org/10.1016/j.childyouth.2022.106373

Meyers, L. S., Gamst, G., & Guarino, A. J. (2017). *Applied multivariate research: Design and interpretation* (Third Edition). SAGE.

Miles, M. B., & Huberman, A. M. (1994). *Qualitative data analysis: An expanded sourcebook*. Sage.

Neophytou, E., Manwell, L. A., & Eikelboom, R. (2021). Effects of excessive screen time on neurodevelopment, learning, memory, mental health, and neurodegeneration: A scoping review. *International Journal of Mental Health and Addiction*, *19*(3), 724–744. https://doi.org/10.1007/s11469-019-00182-2

Özdemir, D., & Arpacıoğlu, S. (2020). Effect of social media use, health perception and health search behavior on the coronavirus fear *Current Approaches in Psychiatry*, *12*, 364-381. https://doi.org/10.18863/pgy.803145

Pallant, J. (2016). SPSS survival manual: A step by step guide to data analysis using IBM SPSS (6th edition). McGraw Hill Education.

Patton, M.Q. (2002). Qualitative research and evaluation methods (3rd Ed.). London: Sage Publications, Inc

Peper, E., & Harvey, R. (2021). Causes of techstress and 'technology-associated overuse' syndrome and solutions for reducing screen fatigue, neck and shoulder pain, and screen addiction. *Townsend Letter*. https://www.townsendletter.com/article/459-techstress-how-technology-is-hurting-us/

Potas, N., Açıkalın, Ş. N., Erçetin, Ş. Ş., Koçtürk, N., Neyişci, N., Çevik, M. S., & Görgülü, D. (2022). Technology addiction of adolescents in the COVID-19 era: Mediating effect of attitude on awareness and behavior. *Current Psychology*, *41*(4), 1687–1703. https://doi.org/10.1007/s12144-021-01470-8

Rideout, V., Lauricella, A., & Wartella, E. (2011). Children, media, and race: Media use among White, Black, Hispanic, and Asian American children. *Evanston, IL: Center on Media and Human Development, School of Communication, Northwestern University*.

Rosen, L. D., Whaling, K., Carrier, L. M., Cheever, N. A., & Rokkum, J. (2013). The Media and Technology Usage and Attitudes Scale: An empirical investigation. *Computers in Human Behavior*, *29*(6), 2501-2511. https://doi.org/10.1016/j.chb.2013.06.006

Rosenfield, M. (2016). Computer vision syndrome (aka digital eye strain). *Optometry in practice*, *17*(1), 1-10.

Saritepeci, M. (2021). Multiple screen addiction scale: validity and reliability study. *Instructional Technology and Lifelong Learning*, *2*(1), 1-17. https://doi.org/10.52911/itall.796758

Serenko, A., & Turel, O. (2020). Directing technology addiction research in information systems: Part I. Understanding behavioral addictions. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems*, *51*(3), 81-96. https://doi.org/10.1145/3410977.3410982

Serra, G., Lo Scalzo, L., Giuffrè, M., Ferrara, P., & Corsello, G. (2021). Smartphone use and addiction during the coronavirus disease 2019 (COVID-19) pandemic: Cohort study on 184 Italian children and adolescents. *Italian Journal of Pediatrics*, *47*(1), 150. https://doi.org/10.1186/s13052-021-01102-8

Servidio, R., Bartolo, M. G., Palermiti, A. L., & Costabile, A. (2021). Fear of COVID-19, depression, anxiety, and their association with Internet addiction disorder in a sample of Italian students. *Journal of Affective Disorders Reports*, *4*, 100097. https://doi.org/10.1016/j.jadr.2021.100097

Shek, D. T. L., Yu, L., Leung, H., Wu, F. K. Y., & Law, M. Y. M. (2016). Development, implementation, and evaluation of a multi-addiction prevention program for primary school students in Hong Kong: The B.E.S.T. teen program. *Asian Journal of Gambling Issues and Public Health*, *6*(1), 5. https://doi.org/10.1186/s40405-016-0014-z

Sigman, A. (2014). Virtually addicted: Why general practice must now confront screen dependency. *British Journal of General Practice*, *64*(629), 610-611. https://doi.org/10.3399/bjgp14X682597

Stevens, J. (2002). *Applied multivariate statistics for the social sciences*. Lawrence Erlbaum Associates.

Streiner, D. L. (1994). Figuring out factors: The use and misuse of factor analysis. *The Canadian Journal of Psychiatry*, *39*(3), 135-140. https://doi.org/10.1177/070674379403900303

Tabachnick, B. G., & Fidell, L. S. (2007). *Using multivariate statistics*. Pearson/Allyn & Bacon.

Turel, O., Serenko, A., & Giles, P. (2011). Integrating technology addiction and use: An empirical investigation of online auction users. *MIS Quarterly*, *35*(4), 1043-1061. https://doi.org/10.2307/41409972

TurkStat. (2021). *Survey on Information and Communication Technology (ICT) Usage in Households and by Individuals*. https://data.tuik.gov.tr/Bulten/Index?p=Survey-on-Information-and-Communication-Technology-(ICT)-Usage-in-Households-and-by-Individuals-2021-37437&dil=2

United Nations Educational Scientific and Cultural Organization [UNESCO] (2020). *Education: From disruption to recovery*. UNESCO. https://en.unesco.org/covid19/educationresponse

Uzun, A. M., & Kilis, S. (2019). Does persistent involvement in media and technology lead to lower academic performance? Evaluating media and technology use in relation to multitasking, self-regulation and academic performance. *Computers in Human Behavior*, *90*, 196-203. https://doi.org/10.1016/j.chb.2018.08.045

We Are Social. (2022). *Digital 2022: Another year of bumper growth*. We Are Social UK. https://wearesocial.com/uk/blog/2022/01/digital-2022-another-year-of-bumper-growth-2/

Winther, D. K., & Byrne, J. (2020). *Rethinking screen-time in the time of COVID-19*. Unicef for every child. https://www.unicef.org/globalinsight/stories/rethinking-screen-time-time-covid-19

Young, K. S. (1998). *Caught in the net: How to recognize the signs of internet addiction--and a winning strategy for recovery*. John Wiley & Sons.

Zhang, S., Shen, Y., Xin, T., Sun, H., Wang, Y., Zhang, X., & Ren, S. (2021). The development and validation of a social media fatigue scale: From a cognitive-behavioral-emotional perspective. *PLOS ONE*, *16*(1), e0245464. https://doi.org/10.1371/journal.pone.0245464

Zheng, X., & Lee, M. K. O. (2016). Excessive use of mobile social networking sites: Negative consequences on individuals. *Computers in Human Behavior*, *65*, 65-76. https://doi.org/10.1016/j.chb.2016.08.011

Appendix 1 Screen Fatigue Scale

(1/5, strongly disagree / strongly agree)

(1) My eyes hurt when I stay in front of the screen for a long time.
(2) My eyes water when I stay in front of the screen for a long time.
(3) I get a headache when I stay in front of the screen for a long time.
(4) I get dizzy when I stay in front of the screen for a long time.
(5) I have pain in my fingers and arm when I stay in front of the screen for a long time.
(6) I get numbness and tingling in my body when I stay in front of the screen for a long time.
(7) I experience back pain when I stay in front of the screen for a long time.
(8) My neck hurts when I stay in front of the screen for a long time.
(9) I get sleepy when I stay in front of the screen for a long time
(10) I cannot produce practical solutions to problems when I stay in front of the screen for a long time.
(11) I become pessimistic when I stay in front of the screen for a long time.
(12) My perception slows down after a certain period when I stay in front of the screen for a long time.
(13) When I stay in front of the screen for a long time, the ratio of remembering things decreases.
(14) I have difficulty concentrating my thoughts on a subject when I am in front of the screen for a long time.
(15) I want fresh air if I spend a long time in front of the screen during the day.
(16) If I spend a long time in front of the screen during the day, I move away from the TV, tablet, or phone to avoid further exposure to the screen.
(17) I need to rest my eyes when I stay in front of the screen for a long time.
(18) On days when I am exposed to the screen for a long time, I would like to engage in activities that will allow me to get away from the screen.
(19) On days when I stay in front of the screen for a long time, I need to move and do sports.
(20) When I stay in front of the screen for a long time, I want to relax by doing my hobbies.
(21) If I spend a long time in front of the screen during the day, digital goods are no longer as attractive as they used to be.
(22) If I spend a long time in front of the screen during the day, my enjoyment of the games I play decreases.
(23) If I spend a long time in front of the screen during the day, my enjoyment of the videos I watch decreases.
(24) If I spend a long time in front of the screen during the day, the enjoyment I get from the TV series/movies I watch decreases.

Note. Items 1-9 - Physical Symptoms, Items 10-14 - Cognitive Symptoms, Items 15-20 Behavioral Symptoms, Items 21-24 Affective Symptoms