Published in the USA
Media Education (Mediaobrazovanie)
Has been issued since 2005
E-ISSN 1994-4195
2022. 18(3): 481-490

DOI: 10.13187/me.2022.3.481
https://me.cherkasgu.press

Smartphone Addiction Scale-Short Version (SAS-SV) among Mexican Adolescents: A Network Psychometric Approach

Jacob Owusu Sarfo [a, *], Arturo García-Santillán [b], Rafael Valdece Sousa Bastos [c], Priscilla Yeye Adumoah Attafuah [d]

[a] University of Cape Coast, Cape Coast, Ghana
[b] Universidad Cristóbal Colón, Veracruz, Mexico
[c] São Francisco University, São Paulo, Brazil
[d] University of Ghana, Legon, Accra, Ghana

Abstract

The original Smartphone Addiction Scale-Short Version (SAS-SV) was developed and validated using adolescents from South Korea. Although researchers often adapted SAS-SV into Spanish and used it among Mexican populations, there is no extensive psychometric report on the scale in current literature among adolescents in high schools. In this study, we sought to report on the psychometricproperties of the SAS-SV with Mexican adolescents in the metropolitan area of Veracruz-Boca del Río. High school students ranging in age from 14 to 18 (M = 16.04, SD = 1.2, 50.63 % male, 49.36 % female, N = 158) completed the Spanish version of the SAS-SV. Based on robust analytical procedures and standardised theories, we reduced the original 10 items to 7 and conducted a network analysis to see the relationship between the reduced items. Our reduced scales indicate high internal consistency and goodness of fit of the confirmatory factor analysis statistics. Our 7-item SAS-SV (Mexican-Spanish version) offers a viable and parsimonious opportunity to measure smartphone addictions among adolescents. Our study has implications for research, adolescent mental health and policy.

Keywords: psychometric properties, network analysis, smartphone addiction scale-short version,mokken scale analysis,mexican adolescents.

1. Introduction

The rise in technology paved the way for smartphones use, especially among adolescents (Anwar et al., 2021; Cerda López, 2016; Valle et al., 2017). Although smartphones are valuable technological devices, problematic use could negatively affect health, academic, career output, and social interactions (Anwar et al., 2021; Cudjoe, 2018; Lee, Shin, 2017; Yang et al., 2016). Frequent use of a substance or item such that the individual feels some level of craving in the absence of it is termed addiction (Lapierre, 2020; Uddin et al., 2018; Zahid, 2021). Thus, the frequent use of smartphones can be addictive as one can stay glued to them, exploring every social application (Berthon et al., 2019; Lapierre, 2020; Uddin et al., 2018). With internet connectivity, these phones have features to perform many fancy activities.

Comparatively, the growing numbers of teenagers and individuals between 20 and 30 years are higher in internet addiction than those above 30 years, implying that this situation may deteriorate in the future. Recently, manufacturers have developed various applications and phone

* Corresponding author
E-mail addresses: jacob.sarfo@ucc.edu.gh (J.O. Sarfo)

types daily to entice these individuals and provide a comfortable lifestyle (Amankwaa, Blay, 2018; Lukoff et al., 2018). Some individuals have their world virtually on their smartphones (Heitmayer, Lahlou, 2021). From financial transactions, food requests, transportation applications, and emails, to social media (WhatsApp, Twitter, Instagram, etc.) handles (Amankwaa, Blay, 2018), the click of a button is all one needs to connect with information and the world.

The rapid change in human interaction, information seeking and entertainment on the internet via social media cannot be underestimated (Cudjoe, 2018; Lee, Shin, 2017). A typical example was seen on October 4th, 2021,as social network Facebook and its holdings, WhatsApp, Instagram, Messenger, Mapillary, and Oculus,came to a halt. There was no means of communication through these (Andrews, (2021). The youth who have become addicted to smartphones had their lives halted (Andrews, (2021).Thus, there is a disruption in the activities of daily living and essential physiologic needs like rest and sleep, as smartphone addiction can make one unconsciously ignore them (Amankwaa, Blay, 2018;Heitmayer, Lahlou, 2021; Kim et al., 2020). The negative consequences surrounding smartphone addiction, especially among young people, have increased the number of studies on smartphone use and the development and validation of scales to assess it (Andrade et al., 2020;Vintilă et al., 2021).

The most commonly used assessment tools for detecting smartphone addiction currently are the Smartphone Addiction Scale (SAS) and its short form (SAS-SV). A population of South Korean adults was first used to validate the 33-item SAS (Kwon et al., 2013a), while the 10-item SAS-SV was validated using South Korean adolescents (Kwon et al., 2013b). Following its initial development, researchers have validated the SAS among Italian adolescents and young adults (De Pasquale et al.,2017), Iranian university students (Kheradmand et al., 2019), Brazilian adolescents (Andrade etal., 2020), American adults (Harris et al., 2020), and Romanian students (Vintilăet al., 2021). Furthermore, the Arabic (Vally, Alowais, 2020) and Chinese versions (Liu, Ma, 2018) have also undergone validation.

Based on the assumption that practitioners and researchers prefer valid and reliable brief scales to lengthy ones, the use and validation of SAS-SV are gaining much popularity too. Consequently, researchers have validated the SAS-SV among Egyptian adolescents (Fathalla, 2019), Turkish adolescents (Akın et al., 2014), Indonesian Junior High School students (Arthy et al., 2019), Nigerian undergraduates (Akpunne, Akinnawo, 2018), Spanish and French-speaking adults in Belgium (Lopez-Fernandez, 2017), and Arabic version among Moroccan adults (Sfendla et al., 2018). Although SAS-SV validation was done using Mexican undergraduate students (Escalera-Chávez, Rojas-Kramer, 2020), little is known about its psychometric properties amongsenior high school students in Mexico. In addition to this gap, a study involving 244 Mexican upper-middle-level studentsfound that 95.4 % used mobile phones with a daily number of calls rangingbetween one and five for 63.5 % of the participants (Cerda López, 2016). As the number of adolescents using smartphones in Mexico increases, it is crucial to explore the psychometric propertiesof SAS-SV among them.

Our study aims to explore the psychometric properties of the Smartphone Addiction Scale (SAS) amonga Mexican adolescent high school sample. Additionally, we used robust analytical procedures and standardised theories to reduce the original SAS-SV items from 10 to 7.

2. Materials and methods

Sample

Participants in this study were adolescents (n = 158) enrolled at High schools in the metropolitan area of Veracruz-Boca del Río who owned smartphone devices. Participants consisted of 50.63 % males and 49.37 % females between the ages of 14 to 18 (M = 16.04, SD = 1.2).

Instrument

We adopted the 10-item SAS-SV to measure the smartphone addiction risk of adolescents (Kwon et al., 2013b), which was adapted and translated by Lopez-Fernandez (Lopez-Fernandez, 2017) into Spanish. The SAS-SV measures daily-life disruption, positive anticipation, withdrawal, cyberspace-oriented relationships, overuse, and toleranceon a 6-point scale [ranging from 1 (strongly disagree) to 6 (strongly agree)] (Kwon et al., 2013b).

The overall score ranges from 10 to 60, with a score of 60 or above indicating "smartphone addiction" within the past year. With a Cronbach's alpha of 0.91, the initial SAS-SV demonstrated highly respectable internal consistency (Lopez-Fernandez, 2015). Males and females are given different weights on the scale. Males who score more than 31 points are classified as addicted, while those who score between 22 and 31 are considered high risk. Females are categorised at high risk between 22 and 33 and addicts above 33 (Escalera-Chávez, Rojas-Kramer, 2020). For data collection purposes, we collected information on SAS-SV, sex, and age of participants.

Data Collection

We collected face-to-face surveys from adolescents attending high schools in Veracruz-Boca del Río, Mexico. The research was conducted following Institutional approvals, parental (including legal representatives or guardians),and participants' consent were sought before data collection. Additionally, our study adhered to all required ethics for human research as enshrined in the Helsinki Declaration.The data collection process lasted between January and February 2020.

Data Analysis

Mokken Scale Analysis

A nonparametric Item Response Theory using Mokken Scale Analysis (MSA) was conducted following data screening and management. The advantage of such a method is that its calculus deals with ordinal item sum scores to generate estimates of latent traits of the sample respondents (Mokken, 1971). This procedure is acceptable because, asymptotically, the sum scores tend to be closer to the true score (Sijtsma,Molenaar, 2002). In addition, it tests three assumptions (unidimensionality, local independence, and latent monotonicity) from parametric Item Response Theory. First, unidimensionality is the idea that only a latent trait of individuals interacts with a latent feature of the items. Second, local independence is the idea that the correlation, or dependence, observed between items is explained exclusively by θ (the latent trait), and multidimensional models represent a breach of this assumption. Third, latent monotonicity (distinguished from observed monotonicity) represents the idea that if the individual has more of the latent trait, his probability of giving a correct answer, or higher on a scale, should also increase.

From the perspective of MSA, the dimensionality analysis is performed through the Automated Item Selection Procedure (AISP) (Mokken, 1971; Sijtsma,Molenaar, 2002). The AISP uses the individual item scalability coefficient to select the most representative item of the dimension and then uses the item pair scalability coefficient to choose the largest subset of items measuring the same attribute (Mokken, 1971). After selecting the best items for the first dimension, unselected items are tested, in a second step, to compose a second subscale and other subscales until it is no longer possible to allocate any items to any subscale. For this study, we implemented a genetic algorithm because it performs best in recovering the correct dimensionality of scales (Straat et al., 2013). As a rule-of-thumb, Straat et al. (Straat et al., 2013) also identified that the scalability coefficient of item pairs using the best item as a reference should not be less than 0.30. However, Sijtsma and Molenaar (Sijtsma, Molenaar, 2002) suggest that it is necessary to use several possible limits for the relationship with the best item, starting with a value of 0.30, to guarantee greater richness in the analysis.

The manifest monotonicity test proposed by Junker and Sijtsma (2000) involves performing a regression between the scores of individual items and the residual scores (rest scores), which are obtained by omitting the selected item from the total test score. A problem with using residual scores to test latent monotonicity is that the number of respondents at different score levels can be very small (Sijtsma, Molenaar, 2002). Grouping respondents overcome this problem with adjacent residual scores until a minimum proportion of individuals per score is greater than a pre-defined criterion. Using as default for such criterion max (n/30.50; given that our sample consisted of 158 respondents), generally robust results would be reached (Sijtsma, Molenaar, 2002). As MSA is a nonparametric approach, it does not establish an Item Response Function like the ones from parametric Item Response Theory to relate items to latent variables.

Wefurther tested in this paper the assumption of non-intersection of item response functions using rest scores. In addition to Cronbach's Alpha (Cronbach, 1951) and Guttman's Lambda 2 (Guttman, 1945), we assessed the reliability of the scale through the rho or Molenaar and Sijtsma (MS) reliability statistic, which is an unbiased estimator of test-score reliability (Mokken, 1971; Molenaar, Sijtsma, 1984; Molenaar, Sijtsma, 1988). All the MSA and reliability analyses were made using R (R Core Team, 2021), using the Mokken package (Van der Ark, 2012).

Redundant Items

Item standard deviations were examined with an exclusion criterion of below 2.5 standard deviations since small-variance items can influence the final estimates of the network (Mullarkey et al., 2018). We also conducted this analysis using the network tools package (Jones, 2020).

Confirmatory Factor Analysis

We used the R software's (R Core Team, 2021) lavaan package (Rosseel, 2012) to perform a Confirmatory Factor Analysis for the single factor model and a Diagonally Weighted Least Squares estimate. The goodness of fit of the model was assessed using the following combination of fit statistics: chi-squared (χ^2), Tucker-Lewis Index (TLI), Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and the Standardised Root Mean Square Residual (SRMR). In line with Brown's (2015) recommendations, cut-off values of 0.90 for CFI and TLI, 0.08 for RMSEA, and SRMR 0.08 indicate a good fit for any given model.

Network Psychometrics

Finally, we performed a network analysis to see the relationship between items. Initially, we estimated an undirected network structure using the scale items. Such a network uses nodes (ordinal respondent scores) and edges (associations among scores). We employed a graphical lasso procedure that estimates a network where the edges are partial correlation coefficients. In addition, we controlled for false-positive edges using the least absolute shrinkage and selection operator (Lasso; Tibshirani, 1996). Furthermore, the shrinkage parameter was chosen to minimise the extended Bayesian Information Criterion (Chen, Chen, 2008). Our analysis was based on cor_auto from the q graph package.

Additionally, we estimated the centrality of all items using note strength (the sum of all associations a given node exhibits with all other nodes), betweenness (the degree to which a node lies on the shortest path between two other nodes), closeness (sum of distances from one node to all other nodes), and Expected Influence (takes into account negative associations among nodes) (Opsahl et al., 2010; Robinaugh et al., 2016). Subsequently, power analysis for the estimated networks extracted three indices: True-estimated network correlation, sensitivity (true positives rate), and specificity (true negatives rate) (Epskamp, Fried, 2018). Our overall sample in Figure 1 shows a high correlation (around 0.90) and specificity values (around 60 %), while sensitivity (around 100 %). This analysis was made in R, using *q graph and boot net* (Epskamp et al., 2017).

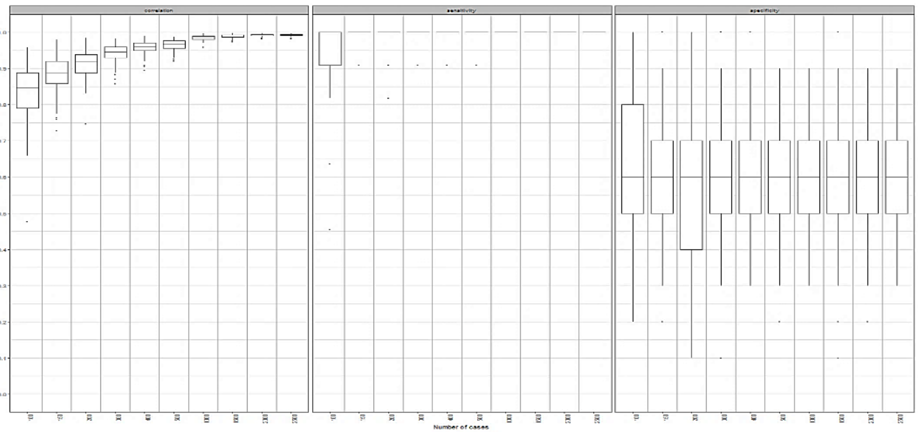

Fig. 1. Power Analysis for the Reduced Smartphone Addiction

3. Discussion and Results

First, we conducted a Mokken Scale Analysis with all 10 items of the Smartphone Addiction Scale. Table 1 shows the analysis of dimensionality of this scale, where, based on Sijtsma and Molenaar (Sijtsma, Molenaar 2002) 0.30 cut-off point, items X1 and X2 should be excluded from further analysis. In addition, we decided to maintain the items X3, X4, X5, X6, X7, X8, X9, and X10 for the next assumption test.

Table 1. Analysis of Dimensionality of the Smartphone Addiction Scale

	Scalability Index (Hj)										
Item	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8
X1											
X2											
X3	1	1	1	1	1	1	2				
X4	1	1	1	1		1					

X5	1	1	1								
X6	1	1	1	1	1	1	2				
X7	1	1	1	1	1	2	1	1	1	1	1
X8	1	1	1	1	1	2	1	1	1	1	1
X9	1	1	1	1	1						
X10	1	1	1								

As for Table 2, the first thing to note is that no monotonicity violation was observed. In part, this probably occurred given that the scalability coefficient, used in the AISP, tends to maintain items that are monotonic with their size (Sijtsma, Molenaar, 2002). However, the AISP will not always select only monotonic items, which justifies this analysis. We conducted the next assumption test with these items based on this analysis.

Table 2. Analysis of Manifested Monotonicity in the Smartphone Addiction Scale

Item	Hj	AC	Vi	MaxVi	Zmax	#zsig
X3	0.49	3	0	0	0	0
X4	0.46	1	0	0	0	0
X5	0.41	3	0	0	0	0
X6	0.47	3	0	0	0	0
X7	0.52	3	0	0	0	0
X8	0.51	2	0	0	0	0
X9	0.49	3	0	0	0	0
X10	0.40	2	0	0	0	0

Note. H_j is the scalability of each item; AC is the quantity of active residual scores pairs; Vi is the number of monotonicity violations; MaxVi is the biggest monotonicity violation; Zmax is the z score of the maximum violation; Zsig is the significance of this violation.

Again, we observed in Table 3 that no item that followed the AISP and Monotonicity results showed an intersection of item response functions. Regarding redundant items, items X8 and X9 showed less than 25 % of different correlations, suggesting that one of those items should be removed. We decided to remove item X8 because it has less generalizability due to its content being specifically about Facebook and Twitter.

Table 3. Non-Intersection of Item Response Functions Analysis for Smartphone Addiction Scale

Item	Hj	AC	Vi	MaxVi	Zmax	Zsig
X3	0.49	63	2	0.05	0.75	0
X4	0.46	63	4	0.07	1.55	0
X5	0.41	63	6	0.10	1.55	0
X6	0.47	63	2	0.06	0.59	0
X7	0.52	63	1	0.06	0.59	0
X8	0.51	63	3	0.08	1.55	0
X9	0.49	63	4	0.10	1.21	0
X10	0.40	63	4	0.06	0.79	0

Note: H_j is the scalability of each item; AC is the quantity of active residual scores pairs; Vi is the number of monotonicity violations; MaxVi is the biggest monotonicity violation; Zmax is the z score of the maximum violation; Zsig is the significance of this violation.

Based on the previous results, we conducted a confirmatory factor analysis with the remaining items to know more information about the scale. The goodness of fit of the confirmatory factor analysis had the following statistics: χ^2 (14, N = 158) = 13.43, p = .49; CFI = 1.00; TLI = 1.00;

RMSEA = 0.000 (CI 90% 0.000 - 0.074); SRMR = 0.057. According to Brown's (2015) recommendation, all goodness of fit statistics showed good results. Reliability estimates of the reduced scale showed the scale has good internal consistency (MS = 0.82; Cronbach's Alpha = 0.81; Guttman's Lambda 2 = 0.82).

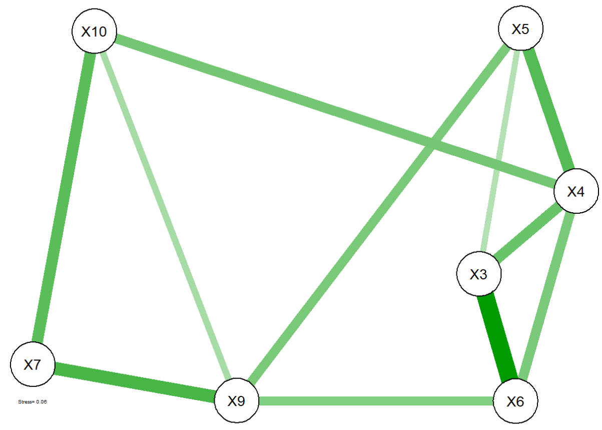

Fig. 2. Network Structure of the Reduced Smartphone Addiction Scale

Next, the network structure of our scale without those items is in Figure 2, while magnitudes can be seen in Table 4. Network centrality can be seen in Figure 3 and their values in Table 5.

Table 4. Network Magnitudes of the Reduced Smartphone Addiction Scale

	X3	X4	X5	X6	X7	X9	X10
X3	0	0.25	0.13	0.42	0	0	0
X4	0.25	0	0.28	0.22	0	0	0.23
X5	0.13	0.28	0	0	0	0.22	0
X6	0.42	0.22	0	0	0	0.20	0
X7	0	0	0	0	0	0.30	0.27
X9	0	0	0.22	0.20	0.30	0	0.15
X10	0	0.23	0	0	0.27	0,15	0

We can see that item X4 is the most influential in the network because it presents the higher Expected Influence, Strength, Closeness and Betweenness. In addition, items X9 and X8 are the second and third most influential items, respectively. These items had the second and third higher Expected Influence, Strength, Closeness and Betweenness.

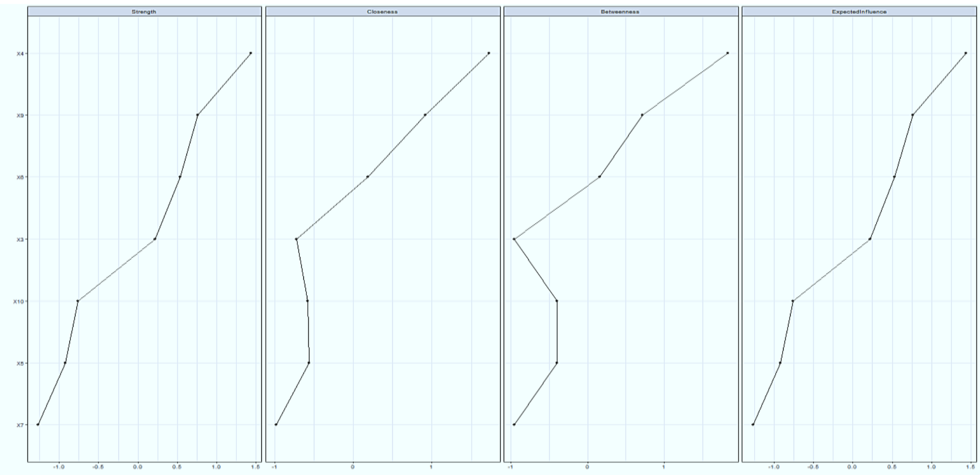

Fig. 3. Network Centrality Estimates for the Reduced Smartphone Addiction Scale

Table 5. Network centrality values of the Reduced Smartphone Addiction Scale

Item	Strength	Betweenness	Closeness	Expected Influence
X3	0.22	-0.95	-0.72	0.22
X4	1.44	1.83	1.73	1.44
X5	-0.92	-0.40	-0.56	-0.92
X6	0.53	0.16	0.19	0.53
X7	-1.27	-0.95	-0.98	-1.27
X9	0.76	0.71	0.92	0.76
X10	-0.76	-0.40	-0.58	-0.76

Reduced Smartphone Addiction Scale (7-Item SAS-SV)

Seven-Item SAS-SV is a 6-point scale [ranging from 1 (strongly disagree) to 6 (strongly agree)]. See Table 6 for the final items in English.

Table 6. Seven-Item SAS-SV

1	Feeling pain in the wrists or at the back of the neck while using a smartphone
2	Won't be able to stand not having a smartphone
3	Feeling impatient and fretful when I am not holding my smartphone
4	Having my smartphone in my mind even when I am not using it
5	I will never give up using my smartphone even when my daily life is already greatly affected by it
6	Using my smartphone longer than I had intended
7	The people around me tell me that I use my smartphone too much

4. Conclusion

To conduct our network psychometric analyses, we collected face-to-face surveysusing a 10-item SAS-SV (Kwon et al., 2013b), adapted and translated into Spanish by Lopez-Fernandez (2017) among adolescents attending high school schools in Veracruz-Boca del Río, Mexico. To our knowledge, the Mexican (Spanish) SAS-SV version among teenagers offered reliable psychometric findings within acceptable bounds. This reduced version (7-item SAS-SV) can be used to assess the prevalence of smartphone addiction among teenagers in Mexico and other South American cultures. The unpredictable demographic characteristics, as well as a small sample size of 158, are the study's limitations. As a result, this Mexican (Spanish) version was thought to be useful for diagnosing smartphone addiction in youths between the ages of 14 and 18. Regarding the traits of the participants, more research has to be done. Also, studies with larger sample sizes across countries in South America would be needed to provide a broader view of the problem in future.

5. Acknowledgements

We acknowledge the management, teachers, parents, and students who supported our study. Conflict of interests: The authors declare that they have no conflict of interest. Funding Sources: None.

References

Akın et al., 2014 – *Akın, A., Altundağ, Y., Turan, M.E., Akın, U.* (2014). The validity and reliability of the Turkish version of the smart phone addiction scale-short form for adolescent. *Procedia-Social and Behavioral Sciences*. 152: 74-77.

Akpunne, Akinnawo, 2018 – *Akpunne, B.C., Akinnawo, O.E.* (2018). Validation of smartphone addiction scale–short version on Nigerian university undergraduates. *International Journal of Computer Science and Mobile Computing*. 7(11): 136-141.

Amankwaa, Blay, 2018 – *Amankwaa, E.F., Blay, K.B.* (2018). Cities at risk? Exploring the synergies between smartphones and everyday vulnerabilities. *Cities*. 83: 129-139.

Andrade et al., 2020 – *Andrade, A.L.M., Scatena, A., Martins, G.D.G., de Oliveira Pinheiro, B., da Silva, A.B., Enes, C.C., ... Kim, D.J.* (2020). Validation of smartphone addiction scale–Short version (SAS-SV) in Brazilian adolescents. *Addictive Behaviors*. 110: e106540.

Andrews, 2021 – *Andrews, A.* (2021). A revealing blackout: The Facebook shutdown of October 4th. [Electronic resource]. URL: https://theath.ca/arts-culture/a-revealing-blackout-the-facebook-shutdown-of-october-4th/

Anwar et al., 2021 – *Anwar, S., Saeed, R., Danish, S.H., Azhar, F.* (2021). Impact of smartphones on physical and psychosocial well-being of children and adolescent. *Asian Journal of Advanced Research and Reports*. 15(4): 6-14.

Arthy et al., 2019 – *Arthy, C.C., Effendy, E., Amin, M.M., Loebis, B., Camellia, V., Husada, M.S.* (2019). Indonesian version of addiction rating scale of smartphone usage adapted from smartphone addiction scale-short version (SAS-SV) in junior high school. *Open Access Macedonian Journal of Medical Sciences*. 7(19): 3235-3239.

Berthon et al., 2017 – *Berthon, P., Pitt, L., Campbell, C.* (2019). Addictive devices: A public policy analysis of sources and solutions to digital addiction. *Journal of Public Policy & Marketing*. 38(4): 451-468.

Brown, 2015 – *Brown, T.A.* (2015). Confirmatory factor analysis for applied research. Guilford publications.

Cerda López, 2016 – *Cerda López, C.E.* (2016). Uso del teléfonocelularenestudiantes de nivelmedio superior. Universidad Autónoma de Nuevo León. Ph.D. Dis.

Chen, Chen, 2008 – *Chen, J., Chen, Z.* (2008). Extended Bayesian information criteria for model selection with large model spaces. *Biometrika*. 95(3): 759-771.

Cronbach, 1951 – *Cronbach, L.* (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*. 16: 297-334.

Cudjoe, 2018 – *Cudjoe, J.* (2018). Is internet a family divide tool in Africa? *Africa: History and Culture*. 3: 28-30.

De Pasquale et al., 2017 – *De Pasquale, C., Sciacca, F., Hichy, Z.* (2017). Italian validation of smartphone addiction scale short version for adolescents and young adults (SAS-SV). *Psychology*. 8(10): 1513-1518.

Epskamp et al., 2018 – *Epskamp, S., Borsboom, D., Fried, E.I.* (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods*. 50(1): 195-212.

Epskamp, Fried, 2018 – *Epskamp, S., Fried, E.I.* (2018). A tutorial on regularised partial correlation networks. *Psychological methods*. 23(4): 617-634.

Escalera-Chávez, Rojas-Kramer, 2020 – *Escalera-Chávez, M.E., Rojas-Kramer, C.A.* (2020). SAS-SV Smartphone Addiction Scale in Mexican University Students. *Education Research International*. 2020: e8832858.

Fathalla, 2019 – *Fathalla, M.M.* (2019). Egyptian validation of smartphone addiction scale short version for adolescents (SAS-SV). *Psycho-Educational Research Reviews*. 8(3): 7-10.

Guttman, 1945 – *Guttman, L.* (1945). A basis for analysing test-retest reliability. *Psychometrika*. 10: 255-282.

Harris et al., 2020 – *Harris, B., McCredie, M., Fields, S.* (2020). Examining the psychometric properties of the smartphone addiction scale and its short version for use with emerging adults in the US. *Computers in Human Behavior Reports*. *1:* e100011.

Heitmayer, Lahlou, 2021 – *Heitmayer, M., Lahlou, S.* (2021). Why are smartphones disruptive? An empirical study of smartphone use in real-life contexts. *Computers in Human Behavior*. 116: e106637.

Jones, 2020– *Jones, P.J.* (2020). *Networktools: Tools for identifying important nodes in networks*. R Package Version 1.2.3. [Electronic resource]. URL: https://CRAN.R-project.org/ package=networktools

Junker, Sijtsma, 2000 – *Junker, B.W., Sijtsma, K.* (2000). Latent and manifest monotonicity in item response models. *Applied Psychological Measurement*. 24(1): 65-81.

Kheradmand et al., 2019 – *Kheradmand, A., Amirlatifi, E.S., Sohrabi, M.R., Mazaheri Meybodi, A.* (2019). Validation of the Persian smartphone addiction scale among Tehran university students, Iran. *International Journal of High Risk Behaviors and Addiction*. 8(1): e81176.

Kim et al., 2020 – *Kim, I., Goh, H., Narziev, N., Noh, Y., Lee, U.* (2020). Understanding user contexts and coping strategies for context-aware phone distraction management system design. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*. 4(4): 1-33.

Kwon et al., 2013a – *Kwon, M., Lee, J.Y., Won, W.Y., Park, J.W., Min, J.A., Hahn, C., ... Kim, D.J.* (2013a). Development and validation of a smartphone addiction scale (SAS). *PloS One*. 8(2): e56936.

Kwon et al., 2013b – *Kwon, M., Kim D.-J., Cho, H., Yang, S.* (2013b). The Smartphone Addiction Scale: Development and Validation of a Short Version for Adolescents. *PLos One* 8(12): e83558.

Lapierre, 2020 – *Lapierre, M.A.* (2020). Smartphones and loneliness in love: Testing links between smartphone engagement, loneliness, and relational health. *Psychology of Popular Media Culture*. 9(2): 125-134.

Lee, Shin, 2017 – *Lee, W.J., Shin, S.* (2016). A comparative study of smartphone addiction drivers' effect on work performance in the US and Korea. *Journal of Applied Business Research*. 32(2): 507-516.

Liu, Ma, 2018 – *Liu, C., Ma, J.* (2018). Development and validation of the Chinese social media addiction scale. *Personality and Individual Differences*. 134: 55-59.

Lopez-Fernandez, 2017 – *Lopez-Fernandez, O.* (2017). Short version of the Smartphone Addiction Scale adapted to Spanish and French: Towards a cross-cultural research in problematic mobile phone use. *Addictive Behaviors*. 64: 275-280.

Lukoff et al., 2018 – *Lukoff, K., Yu, C., Kientz, J., Hiniker, A.* (2018). What makes smartphone use meaningful or meaningless? *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*. 2(1): 1-26.

Mokken, 1971 – *Mokken, R.J.* (*1971*). A theory and procedure of scale analysis. The Hague: Mouton.

Mokken, 2011 – *Mokken, R.J.* (2011). A theory and procedure of scale analysis. De Gruyter Mouton.

Molenaar, Sijtsma, 1984 – *Molenaar, I.W., Sijtsma, K.* (1984). Internal consistency and reliability in Mokken's nonparametric item response model. *Tijdschrift Voor Onderwijsresearch*. *9*(5): 257-268.

Molenaar, Sijtsma, 1988 – *Molenaar, I.W., Sijtsma, K.* (1988). Mokken's approach to reliability estimation extended to multicategory items. *Kwantitatievemethoden*. 9(28): 115-126.

Mullarkey et al., 2018 – *Mullarkey, M.C., Stewart, R.A., Wells, T.T., Shumake, J., Beevers, C.G.* (2018). Self-dislike and sadness are central symptoms of depression in college students: A network analysis. 24.10.2018. DOI: https://doi.org/10.31234/osf.io/fujmb

Opsahl et al., 2010 – *Opsahl, T., Agneessens, F., Skvoretz, J.* (2010). Node centrality in weighted networks: Generalising degree and shortest paths. *Social Networks*. 32(3): 245-251.

R Core Team, 2021 – *R Core Team* (2021). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. [Electronic resource]. URL: http://www.R-project.org/

Robinaughett al., 2016– *Robinaugh, D.J., Millner, A.J., McNally, R.J.* (2016). Identifying highly influential nodes in the complicated grief network. *Journal of Abnormal Psychology*. 125(6):747-757.

Rosseel, 2012 – *Rosseel, Y.* (2012). lavaan: An R Package for Structural Equation Modeling. *Journal of Statistical Software*. 48(2): 1-36.

Sfendla et al., 2018 – *Sfendla, A., Laita, M., Nejjar, B., Souirti, Z., Touhami, A.A.O., Senhaji, M.* (2018). Reliability of the Arabic smartphone addiction scale and smartphone addiction scale-short version in two different Moroccan samples. *Cyberpsychology, Behavior, and Social Networking*. 21(5): 325-332.

Sijtsma, Molenaar, 2002 – *Sijtsma, K., Molenaar, I.W.* (2002). Introduction to non-parametric item response theory. New York: Sage.

Straat et al., 2013 – *Straat, J.H., van der Ark, L.A., Sijtsma, K.* (2013). Comparing optimisation algorithms for item selection in Mokken scale analysis. *Journal of Classification*. 30: 72-99.

Tibshirani, 1996 – *Tibshirani, R.* (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*. 58(1): 267-288.

Uddin et al., 2018 – *Uddin, I., Baig, A., Minhas, A.A.* (2018). A controlled environment model for dealing with smart phone addiction. *International Journal of Advanced Computer Science and Applications*. 9(9): 578-583.

Valle et al., 2017 – *Valle, J., Godby, T., Paul III, D. P., Smith, H., Coustasse, A.* (2017).Use of smartphones for clinical and medical education.*The Health Care Manager*. 36(3): 293-300.

Vally, Alowais, 2020 – *Vally, Z., Alowais, A.* (2020). Assessing risk for smartphone addiction: Validation of an Arabic version of the smartphone application-based addiction scale. *International Journal of Mental Health and Addiction*. 20: 691-703.

Van der Ark, 2012– *Van der Ark, L.A.* (2012). New Developments in Mokken Scale Analysis in R. *Journal of Statistical Software*. 48(5): 1-27.

Vintilă et al., 2021 – *Vintilă, M., Tudorel, O. I., Goian, C., Bărbat, C.* (2021). Determining the structure of Smartphone Addiction Scale: A bifactor model analysis. *Current Psychology*. 40(3): 1107-1114.

Yang et al., 2016 – *Yang, Z., Asbury, K., Griffiths, M.D.* (2019). An exploration of problematic smartphone use among Chinese university students: Associations with academic anxiety, academic procrastination, self-regulation and subjective wellbeing. *International Journal of Mental Health and Addiction*. 17(3): 596-614.

Zahid, 2021 – *Zahid, A.* (2021). Technology addiction and Its impact on children mental health. Ph.D. Dis.