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Translation and validation of the Arabic version of the Digital Stress Scale (DSS-A) with three Arabic-speaking samples

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Abstract

Objective Given the ubiquitous nature of digital technologies such as smartphones, research has increasingly focused on the health outcomes of prolonged use of such technologies. The Digital Stress Scale (DSS) has been developed recently, but it is currently only available in English and Chinese, and validations in other languages are warranted.

Methods The 24-item DSS was translated into Arabic using the method of translation and back-translation. Using a general population sample ($n = 1069$) from Saudi Arabia, Oman, and Jordan, the psychometric properties of the Arabic DSS (DSS-A) were investigated using higher-order confirmatory factor analysis.

Results The original five-factor structure was replicated for the DSS-A without the need for any modifications such as item deletion or reassignment of items to another factor. Reliability was excellent for the total scale score ($\alpha = 0.92$) as well as for the five subscales (α ranged between 0.81 and 0.91). Convergent validity was supported by significant correlations between the DSS-A and psychological distress.

Conclusion The strong psychometric properties of the DSS-A imply that this scale can now be used with high validity and reliability to explore the role of digital stress and its sub-characteristics in Arabic-speaking populations.

Keywords Digital stress, Digital Stress Scale, Arabic, Translation, Validation, Confirmatory factor analysis

Introduction

In contemporary society, digital devices have become integral to both our personal and professional activities. Particularly, smartphones have made a big impact due to their ability to offer many functions beyond a telephone, thus offering a large range of different communication avenues and facilitating access to a vast array of online resources. Over the past decade, smartphones have quickly reached near-complete market penetration in many parts of the world. Around 20 years ago, one would have heard frequently about the concept of the "digital divide" which describes unequal access to the Internet and computer technologies [1]. With smartphone technology, the extent of the digital divide has substantially diminished. It is projected that by 2028, 5.1 billion

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individuals around the world will own a smartphone [2]. Countries like the USA have seen a consistent rise in smartphone adoption, with user counts in 2023 standing at 310 million and thus more than 90% of the population [3]. In many non-Western countries, the statistics are very similar. In Saudi Arabia, for example, the smartphone penetration rate was more than 90% in 2022 [4]. Given these trends, the impact of the use of smartphone technology has become a topic of significant practical and academic interest.

Even during the era of early mobile phones, concerns have emerged about their potential impact on human communication and social behaviors. While these devices brought undeniable conveniences, allowing users to stay connected and communicate with ease, they also introduced new challenges. Srivastava [5] highlighted the trade-offs between the benefits of constant availability on one hand and drawbacks on the other, such as family fragmentation and privacy issues. As smartphones evolved and offered many more advanced features, these concerns only intensified. The ability for users to share personal photos on social media platforms, for instance, made it easier for others to track their movements, sparking further debates on privacy [6]. Increasingly, however, concerns about mental health implications have been raised. In many countries, there are reports about widespread smartphone addictions, and these trends appear to be worsening [7]. In Saudi Arabia, for example, reports of excessive smartphone use by university students have been reported consistently, with associated objective and perceived negative outcomes for health, academic performance, and social relationships [8–10].

Recent neuroscience work has explored the effects of prolonged digital technology use on brain and cognitive functioning, with mixed results. On the positive side, studies have shown that Internet searching can serve as a form of mental exercise, strengthening neural circuits and potentially delaying cognitive decline [11, 12]. Various apps and computer games have also been explicitly developed to improve memory and other cognitive functions, particularly in older adults. However, the negative consequences are equally compelling. Increased screen time has been linked to symptoms of attention-deficit hyperactivity disorder, impaired emotional and social intelligence, and sleep disruption. In terms of its effects on the brain, therefore, digital technology offers several cognitive benefits but also poses significant risks. Future research is imperative to identify the specific conditions and behaviors that modulate the impact of digital technology on brain health, aiming to discern which factors contribute to either beneficial or detrimental outcomes for different populations [11, 12].

The effects of digital technology and smartphone use on mental health are similarly complex. The link between *problematic* smartphone use and deleterious mental health is clear, as highlighted in systematic reviews and meta-analyses [13–15]. However, since the majority of people engage in use that does not reach problematic levels [14], it is also important to investigate the relationship between smartphone use and mental health in this wider population group. In this instance, the evidence points to a complex web of moderating factors, indicating that the relationship between smartphone use and well-being appears to be more intricate than a straightforward linear association. In a study of 5315 young Swiss men, for example, there was a correlation between time spent on a smartphone and higher rates of psychological distress and attention deficit as well as lower life satisfaction. Contrary to this linear relationship, however, health outcomes were worse among 4.3% of nonusers in this sample [16]. Females have consistently been shown to be more prone to problematic smartphone use [17, 18], although age may be a stronger moderating factor than gender [13], with evidence that the relationship between diminished mental health and smartphone use is stronger among the older users [19, 20]. These effects may also be due to different usage types as research has demonstrated that negative effects tended to be higher in terms of nonsocial and passive use as opposed to social and active engagement with the technology [21–23].

Recognizing the intricate factors that appear to govern the relationship between digital technology use and mental health, Hall et al. [24] developed the Digital Stress Scale (DSS) to provide a rigorous tool for understanding this complexity. The DSS emerged as a comprehensive instrument designed to delve into the multidimensional aspects of digital stress, specifically in the realm of social media. Drawing from the conceptual framework by Steele et al. [25], which identified four core components of digital stress, namely Availability Stress (AS), Approval Anxiety (AA), Fear of Missing Out (FoMO), and Connection Overload (CO), Hall et al. [24] developed an initial set of 53 items after an extensive literature review, and these items underwent iterative refinement through focus-group discussions with high school and college students, resulting in a refined pool of 51 candidate items. After a series of validation studies involving both exploratory and confirmatory factor analyses with diverse samples of young adults and undergraduates, Hall et al. [24] proposed a final 24-item scale grouped into 5 factors. These factors reflect the original four components proposed by Steele et al. [25] but also include an additional factor termed online vigilance (OV). Higher-order confirmatory factor analysis (CFA) concluded that these factors

can be subsumed under an overarching factor that may be labelled *Digital Stress* [24].

The DSS was subsequently translated into Mandarin and validated with two samples of university students in China, and psychometric testing affirmed its reliability and validity for research on digital stress in the Chinese context [26, 27]. Apart from the original English and Chinese versions, no published version of the DSS is available for other languages [28]. The present study aims to translate the DSS into Arabic and evaluate its psychometric properties to enable research on the health impacts of digital stress in the predominantly Arabic-speaking parts of the globe. Given the importance of investigating digital stress in demographically diverse populations, the present study collected samples from the general populations in three Arabic-speaking countries.

Materials and methods

Participants

Of the initial 1214 adults who agreed to participate, 1069 participants completed the DSS and demographic sections. Participants were from Saudi Arabia ($n=577$), Oman ($n=342$), and Jordan ($n=150$). The participants ranged in age from 18 to 70 years, with a mean age of 29.10 years ($SD=9.91$). Most of the respondents ($n=790$; 74%) were female, and 279 (26%) were male. Regarding marital status, 657 (61.5%) were single, 380 (35.5%) were married, 25 (2.3%) were divorced, and 7 (0.7%) were widowed. As for their employment status, 561 (52.5%) were students, 284 (26.6%) were employed, 186 (17.4%) were unemployed, and 38 (3.6%) were retired.

Procedure

Participants were recruited online using convenience sampling via the social media platforms Facebook and X (formerly known as Twitter) as well as student Telegram groups. Prior to completing the questionnaire, participants provided electronic informed consent. No incentives were provided to the participants. Data were collected between June and October 2022, and the study was approved by the authors' university ethics review board.

Measures

The 24-item DSS [24] was used to measure digital stress. The DSS uses a 5-point Likert scale, with responses ranging from 1 (*never*) to 5 (*always*). Participants were instructed to indicate how frequently during the past 7 days they have felt what is expressed in the item statements. The first four items pertain to the AS factor (e.g., "My friends expect me to be constantly available online"), items 5 to 10 are about AA (e.g., "I am nervous about how people will respond to my posts and photos"), items 11 to 14 focus on FoMO (e.g., "I fear my friends are having more rewarding experiences than me"), items 15 to 20 express ideas about CO (e.g., "I have to check too many notifications"), and items 21 to 24 are related to OV (e.g., "I must have my phone with me to know what is going on"). The DSS has been effectively evaluated using both first- and higher-order CFA models, in both its English and Chinese versions, which indicates that scores may be analyzed both as specific subscales as well as an overall total score [28]. The wording of each item on the scale is such that a higher score represents a higher level of digital stress.

In line with established protocols for cross-cultural adaptation, the DSS was translated into Arabic using a step-by-step process as described by Sousa and Rojjanasrirat [29]. Briefly, these steps included the following: (1) translating the English DSS into Arabic by two bilingual speakers, who were fluent in both English and Arabic, independently, (2) comparing the two translations by a third person who was not familiar with the original English version of the DSS and drafting a provisional translation, (3) back-translating the provisional Arabic draft into English by another independent bilingual translator, and (4) comparing the provisional Arabic draft and the back-translated draft and reconciliation of any problematic items. The resulting Arabic version of the DSS (DSS-A) was then piloted with a sample of 20 Arabic-speaking participants recruited online to find out if there were any problems in the perception and understanding of the content of the items. There were no issues to resolve. The pilot-study participants were not included in the analysis reported here. The items of the DSS-A can be found in the supplementary materials.

As a measure of convergent validity, the Kessler Psychological Distress Scale (K10) was used to assess nonspecific psychological distress [30]. The K10 is a widely used measure of the frequency with which respondents experienced symptoms in the past 4 weeks (e.g., nervousness, hopelessness, sadness, worthlessness, and fatigue) [31]. Each item on the K10 was scored on a 5-point Likert-type scale ranging from 1 (*none of the time*) to 5 (*all of the time*. Responses were summed to create a total score, ranging from 10 to 50, with higher scores indicating greater psychological distress. Robust psychometric properties for the K10 have been reported for the original as well as the Arabic version [30–33].

Data analyses

Due to the setup of the online questionnaire that required participants to respond to every item, there were no missing data for participants who completed the DSS-A. A Confirmatory factor analysis (CFA) was performed using the LISREL 8.80 software [34]. The chosen

estimation method was diagonally weighted least squares with polychoric correlations, deemed most suitable for ordinal-level datasets, like those derived from Likert-scale items [35]. This approach is thus designed for data that deviate from a normal distribution, although none of the items of the DSS-A had elevated skewness or kurtosis, with all values falling well into the range of − 1.50 to 1.50.

To assess the disparity between the sample and the fitted covariance matrix, chi-square is typically employed. A model is considered tenable when it yields a nonsignificant chi-square result ($p > 0.05$). However, due to chi-square values potentially becoming inflated with expansive sample sizes [36], the goodness of fit is frequently gauged using alternative indices, namely the comparative fit index (CFI), the root-mean-square error of approximation (RMSEA), and the standardized root-mean-squared residual (SRMR). In this study, a model was deemed well-fitting if the values were $CFI > 0.950$, $RMSEA < 0.060$, and $SRMR < 0.080$, aligning with widely recognized criteria [37, 38].

The analysis examined the five factors (AS, AA, FoMO, CO, and OV) nested within the higher-order five-factor digital stress. In case of misfit as indicated by the fit indices, modification indices were inspected to inform correlation of item error covariances in a subsequent analysis step, provided such correlations were within the same factor. To depict the closeness of the findings to the CFA cut-off values, which hold significance up to two decimals, these values are detailed up to three decimals.

Results

Figure 1 illustrates the subsequent path diagram generated from the CFA depicting a summary of the 5 factor loadings of the 24-item DSS-A. The initial higher-order five-factor model demonstrated the following fit indices: RMSEA of 0.066 (confidence interval: 0.061; 0.071), CFI of 0.976, and SRMR of 0.063. Notably, the RMSEA was slightly above the widely accepted cutoff of 0.06, suggesting potential room for improvement in the model fit.

Subsequent inspection of modification indices was undertaken to identify sources of misfit. Error covariances with modification indices exceeding 100 were particularly considered for potential correlation. Specifically, correlations were observed between the errors of items 11 and 13 and items 11 and 14. Although the modification index also signaled a potential correlation between items 11 and 22, this was disregarded as these items originate from distinct factors. Hence, only correlations without crossing factors were entertained. Upon making these adjustments, the model yielded an improved fit with the following indices: RMSEA dropped to 0.050 (0.044; 0.055), CFI increased to 0.986, and SRMR slightly decreased to 0.062. More so, all individual factor loadings surpassed the 0.70 threshold (Fig. 1). Importantly, the loadings of the individual factors to the overarching higher-order factor were found to be within the range of 0.58 to 0.82. This range solidly supports the notion that these individual factors collectively depict the latent construct aptly termed digital stress.

The overall DSS-A demonstrated robust internal consistency reliability with a McDonald's omega of 0.92, which was in line with a Cronbach's alpha of 0.92 (Table 1). Exploring the individual factors further, both alpha and omega values were very similar and mostly above 0.80. For the factor of FoMO, there was a Cronbach's alpha of 0.82, while the McDonald's omega slightly trailed at 0.79. In addition to values of internal consistency, Table 1 shows means and standard deviations for the total DSS-A and its subscales, alongside values reported for the original English [24] and the Chinese versions [26]. Consistent with these studies, scores were calculated by averaging relevant items for each participant, before calculating a mean score. Compared to the total DSS scores of the English and Chinese versions, the mean for the present Arabic DSS version was significantly lower. However, this difference appears to have been driven by the clearly lower mean value of the present sample on the FoMO subscale. For three of the subscales (AS, AA, and CO), the mean for the present sample was significantly lower than one of the other studies but not the other. For OV, the scores of the present sample were not significantly different from those of the other two studies.

Table 2 presents Pearson's r correlation coefficients for all five factors and the ASS-A total score. There were significant strong correlations between each factor and the full scale, with coefficients spanning from 0.62 to 0.81. In contrast, the inter-factor correlations were more moderate, generally in the region of 0.40 to 0.50. Notably, the correlation between AS and FoMO was the most subdued, registering a coefficient of 0.29. This nuanced relationship suggests distinct underlying aspects characterizing these two specific dimensions of digital stress.

The relationship between age and the total DSS and subscale scores is also shown in Table 2. In all cases, there was a small significant negative correlation. Given that males (M_{age} 33.16, $SD = 11.01$) in this sample were significantly older ($t(418.90) = 7.49$, $p < 0.01$, equal variances not assumed) than females (M_{age} 27.67, $SD = 9.07$), analyses of subscale and total score differences by sex were conducted using an ANCOVA that controlled for age. There was no significant effect by sex for AS and OV (both $F(1, 1066) = 7.20$, $p > 0.05$), but for all remaining subscales (AA, $p < 0.01$; FoMO, $p < 0.01$; CO, $p < 0.05$) and the total

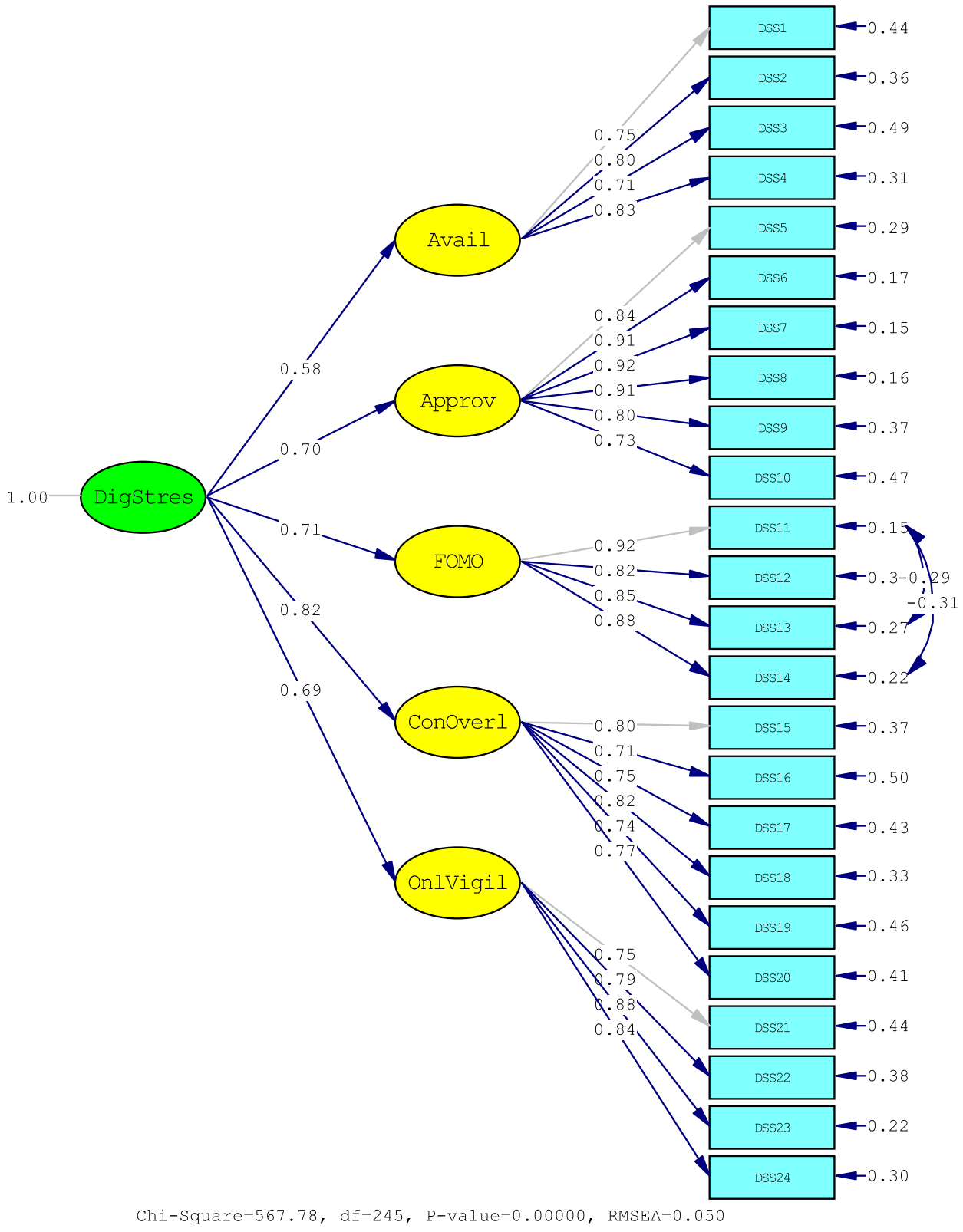

Fig. 1 Model fit of the five-factor model of the DSS-A with a higher-order factor digital stress

Table 1 Indices of internal consistency, means, and standard deviations (*SD*) for the total score of the Arabic DSS and its subscales ($n=1069$). For comparative purposes, mean values are also shown for the English version ($n=735$; [24] and the Chinese version ($n=752$; [26]

Scales	Number of items	Arabic DSS			English DSS [24]	Chinese DSS [26]
		α	*ω*	Mean (*SD*)	Mean (*SD*)	Mean (*SD*)
DSS total	24	0.92	0.92	2.55 (0.74)	2.74 (0.81)**	2.67 (0.76)**
AS	4	0.81	0.82	2.61 (0.94)	2.65 (1.04)	2.85 (1.03)**
AA	6	0.91	0.91	2.55 (1.08)	2.79 (1.08)**	2.56 (1.05)
FoMO	4	0.82	0.79	2.12 (0.93)	2.57 (1.05)**	2.41 (1.05)**
CO	6	0.86	0.86	2.35 (0.92)	2.49 (0.93)**	2.43 (1.00)
OV	4	0.86	0.86	3.21 (1.09)	3.22 (1.04)	3.29 (1.07)

DSS Digital Stress Scale, *AS* Availability stress, *AA* Approval anxiety, *FoMO* Fear of missing out, *CO* Connection overload, *OV* Online vigilance. $^{**}p<0.01$ for comparisons of the means with those of the present study that used the Arabic version of the DSS

Table 2 Pearson's *r* correlation coefficients for DSS-A total and its subscales, K10, and age

	1	2	3	4	5	6	7
1. DSS-A total							
2. AS	0.62*						
3. AA	0.79*	0.31*					
4. FoMO	0.72*	0.29*	0.55*				
5. CO	0.81*	0.41*	0.48*	0.51*			
6. OV	0.71*	0.41*	0.40*	0.34*	0.51*		
7. K10	0.41*	0.19*	0.33*	0.35*	0.32*	0.31*	
8. Age	−0.20*	−0.19*	−0.17*	−0.25*	−0.09*	−0.08*	−0.22*

DSS-A Arabic Digital Stress Scale, *AA* Availability stress, *AA* Approval anxiety, *FoMO* Fear of missing out, *CO* Connection overload, *OV* Online vigilance, *K10* Kessler Psychological Distress Scale. *n* for the K10 was 1030, otherwise 1069 for other variables. $^{*}p<0.01$

scale ($p<0.01$), the differences were significant, with males exhibiting higher values than females.

Lastly, the correlations between psychological stress, as measured by the K10, with the total DSS-A score and the subscales were significant and in the expected directions. Digital stress was moderately positively correlated with psychological distress providing evidence for convergent validity.

Discussion

The aim of this study was to translate and validate an Arabic version of the DSS for assessing digital stress in Arabic-speaking populations. The subsequent results demonstrated that the DSS-A has robust psychometric properties, capturing various dimensions of digital stress consistent with the original English scale [24]. Without the need for deleting any of the 24 items or assigning items to different factors, the DSS-A has high reliability for its subscales as well as the total scale. The use of both subscale scores and the total score can be justified by the excellent fit of the data to a higher-order model. Scores were significantly moderately correlated with a measure of psychological distress, confirming that the DSS-A measures a construct that is related to general psychological distress but distinct from it.

Consistent with many parts of the world [7], prevalent problematic smartphone use in the Middle East has been identified as a major challenge for mental health [39], highlighting the need for more research to understand the factors determining digital stress and how, in turn, this affects mental health. The strong psychometric properties of the DSS-A not only solidify the scale's potential for research application within Arabic-speaking populations but also reinforce its conceptual framework [24, 25]. The observed correlations between the five factors and the total scale were high, suggesting that each factor contributes significantly to the overall construct of digital stress. Some of the previous studies on digital technology use in the Middle East have focused on specific aspects of digital stress, such as FoMO [40, 41], and, therefore, the availability of the Arabic version of the DSS allows for more detailed explorations through its broader coverage of other relevant factors.

The nuanced relationship between the subscales of the DSS is a topic for further investigation. Both Hall et al. [24] and Xie et al. [26] published correlation tables,

which can be compared to the results of the present study (Table 2). In general, the results of the present Arabic version are more similar to the findings by Hall et al. [24] who developed the original English-language version, while the correlations were overall lowest for the Chinese version. For the present Arabic version, the lowest correlation was between AS and FoMO, with a value of $r=0.29$, compared to 0.19 reported by Xie et al. [26]. Longitudinal studies are necessary to investigate to what extent the five factors of the DSS express the construct of DSS or to what extent there may be a causal relationship between these variables such that a factor may be the outcome of another.

The interplay between the factors of digital stress is no doubt also a topic for further cross-cultural work. The present study can be seen as a step toward that goal, through the translation of an Arabic version. Another topic for further investigation is exploring the reasons for the clearly lower score of the present sample on the FoMO subscale compared to the samples from the USA [24] and China [26]. One likely explanation is that the present study used a general population sample, whereas the other studies used samples of university students. More work is required with other general population samples to understand the relationship between aspects of digital stress among each other as well as with other factors.

The fact that, in the present study, the FoMO subscale had the highest negative correlation coefficient with age seems to corroborate the hypothesis that this dimension may be particularly elevated in younger samples such as university students. Another subscale that had an elevated correlation (albeit still relatively small, with $r=-0.17$) was AA. Given that social conformity tends to be more pronounced in younger people [42], this finding is perhaps not very surprising. What may be more surprising, however, is the fact that the US sample [24] had a higher score on the AA subscale than the sample of the present Arabic version and the Chinese version [26]. Even though one might expect that collectivist societies experience a higher level of need for approval from others, it may be that this need is not expressed through online means. Future work is required to explore this effect further in cross-cultural mixed-method studies.

Several limitations need to be noted. Even though the present study attempted to validate the Arabic version of the DSS with participants from the general population, the sampling technique relied on a convenience sample obtained through social media. Even though social media consumption is very high [43], this is likely to have introduced a sampling bias toward individuals whose levels of digital stress may be different from other segments of society. The results regarding the demographic comparisons therefore need to be replicated in the other samples. Additionally, approximately two-thirds of the participants in the present sample were from Saudi Arabia, with the only other representation of Arabic-speaking populations being from Oman and Jordan. The generalizability of these findings to other Arabic-speaking countries will therefore need to be explored.

Conclusions

The purpose of the present study was to translate the DSS [24] into Arabic and test its psychometric properties — a goal that has been achieved. The DSS-A demonstrated very strong psychometric properties that replicated the theoretically founded five-factor structure of the original English DSS. This work enables future research studies to be conducted on digital stress in Arabic-speaking populations. Given that the use of digital devices is also highly pervasive in the Middle East, the present study paves the way to detailed investigations of the potentially harmful negative psychological consequences of digital device use, with the goal of identifying strategies and informing interventions to mitigate such negative effects.

Abbreviations

AA	Approval anxiety
AS	Availability stress
CFA	Confirmatory factor analysis
CFI	Comparative fit index
CO	Connection overload
DSS	Digital Stress Scale
DSS-A	Arabic Digital Stress Scale
FoMO	Fear of missing out
K10	Kessler Psychological Distress Scale
OSF	Open Science Framework
OV	Online vigilance
RMSEA	Root-mean-square error of approximation
SRMR	Standardized root-mean-squared residual

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s43045-023-00387-1.

Additional file 1: Supplementary material. Arabic version of the Digital Stress Scale (DSS-A).

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Authors' contributions

Each author has made a substantial contribution to the study design, data acquisition, data analysis, or interpretation of data or has drafted the work or substantively revised it. Each author has approved the submitted version and has agreed both to be personally accountable for the author's own contributions and to ensure that questions related to the accuracy or integrity of any part of the work, even ones in which the author was not personally involved, are appropriately investigated and resolved, and the resolution documented in the literature.

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Availability of data and materials
The data associated with this manuscript can be found on the Open Science Framework (OSF): https://doi.org/10.17605/OSF.IO/A4XM2.

Declarations

Ethics approval and consent to participate
All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. This study was approved by the authors' university ethics review board. Electronic informed consent was obtained from all individual participants included in the study.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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