Psychiatry Research 279 (2019) 180–185

Contents lists available at ScienceDirect

Psychiatry Research

journal homepage: www.elsevier.com/locate/psychres

"Development and preliminary validation of an image-based instrument to assess depressive symptoms"

Davide Marengo[a], Michele Settanni[a,*], Fabrizia Giannotta[b]

[a] Department of Psychology, University of Turin, Italy
[b] Division of Public Health, School of Health, Care and Social Welfare Mälardalen University, Västerås, Sweden

ARTICLE INFO

Keywords:
Young adults
Measurement
Psychopathology
Depression
Image-based instrument

ABSTRACT

Depression has high social and economic costs, making the reducing of potential barriers to screening of utmost importance. The use of non-verbal, image-based items might help to widen accessibility to depression screenings due to their potentially increased ease of interpretation and language-free nature. In this view, the paper presents two studies exploring the feasibility of assessing depressive symptoms using a set of image-based items consisting of 36 emoji. In study 1, 430 online-recruited young adults participated to investigate whether they ever felt in the way depicted by each emoji during the last week. Results showed that 33 emoji had significant, theoretically coherent correlations with the 10-item version of the Center for Epidemiologic Studies Depression Scale. Next, a subset of 10 emoji were selected for potential inclusion in a brief depression assessment. In study 2, using a sample of 482 young adults, the 10-item emoji-based assessment showed acceptable internal consistency, and theoretically consistent convergent and divergent validity with depressive symptoms, and big-5 personality traits. Further, the emoji-based screening instrument showed remarkable accuracy in identifying individuals showing depression symptoms. Overall, results indicate that the selected emoji represent a promising alternative to text-based items when assessing depressive symptoms among young adults.

1. Introduction

Depression rates are in constant growth in Western countries. Mojtabai et al. (2016) have found that the 12-month prevalence of major depressive episodes increased from 8.7% in 2005 to 11.3% in 2014 in adolescents and from 8.8% to 9.6% in young adults in the US. WHO has estimated that nearly 4 out of 15 people are affected by major depression or some form of depression every year (2013). Moreover, the annual suicide rate is 13.9 per 100 000 on average in the European Region. In spite of the increase of symptomatology, a similar increase in mental health care has not been observed (Mojtabai et al., 2016). This highlights the difficulty of health care services to reach many adolescents and young adults with either a diagnosis or elevated levels of depressive symptoms, and calls for the reduction of potential barriers to widespread screening.

Currently depressive symptoms are often assessed through well-validated questionnaires, i.e. CES-D (Andersen et al., 1994), and BDI (Beck et al., 1996). These instruments have been widely used because they can provide a fast and reliable assessment. However, one limitation that they share with all the text-based tests is that, by relying on the use of verbal items, they may show significant bias when comparing individuals from different cultures (e.g., Mui et al., 2001), or varying in their primary language and education level (for a review, see Teresi et al., 2008). Similar problems have emerged with text-based measures for cognitive skills and personality assessment, where the level of language and education may affect the interpretation of the items and then bias the assessment (e.g., Jones, and Gallo, 2002; Rammstedt et al., 2010; Rolland et al., 1998). Therefore, new tools for measurement that can overcome this limitation are needed to reach as many individuals as possible.

A possible solution for the above-mentioned limitation might consist in the adoption of non-verbal, image-based items. In particular, there is an increased evidence that image-based items might be good measurement tools and they have already been successfully employed in other areas of psychological measurement, such as intelligence (Naglieri, 2003), neuropsychological assessment (for a review, see McCallum, 2003), and personality (Marengo et al., 2017). When it comes to depression, the use of non-verbal, image-based items might ease the interpretation of the items and lower barriers to depression screenings. The use of image-based items may be especially beneficial among young people, due to their increasing preference towards visual-based media (e.g., Marengo et al., 2018; An, 2017), as well as their

* Corresponding author.
E-mail address: michele.settanni@unito.it (M. Settanni).

https://doi.org/10.1016/j.psychres.2019.02.059
Received 17 January 2019; Received in revised form 22 February 2019; Accepted 23 February 2019
Available online 28 February 2019

greater acceptance and use of image-based cues, such as emoji or emoticons, in their day-to-day online communication (e.g., Prada et al., 2018).

There are few studies that have explored the use of image-based cues to assess positive and negative affect, emotions, and feelings, including depressive symptoms. For instance, Settanni and Marengo (2015) have found in a sample of Italian adults that the lower frequency of emoticons expressing positive sentiment in Facebook posts is associated with users' increased emotional distress. More specifically for depression, Lee et al. (2008) explored the use of three specifically devised emoji depicting sad, happy, and neutral facial expressions, as items for the detection of depressive symptoms in Chinese stroke patients. Patients reported about the frequency they experienced having each of the three facial expressions over the past week. Results showed that the sad face item could provide a measure of depression as reliable as a traditional 15-item depression scale. Similarly, Tan et al. (2018) explored used of emoji-based items to assess depressive symptoms among a sample of elderly people from Singapore. Participants rated their mood using an emoji scale ranging from 1 (*most happy face*) to 7 (*most sad face*). Findings showed the emoji-based scale had adequate specificity but lacked in sensitivity in assessing depression. Therefore, the emoji-scale showed good accuracy in identifying individuals showing subclinical depressive symptoms, but showed poor accuracy in detecting individuals with clinical depression, an issue which the authors traced back to the inability of the emoji-scale to measure other relevant domains of the *DSM-IV* criteria for depression (sleep, energy, appetite, etc.) beside that of depressed mood. Therefore, even if limited, there is some emerging evidence that image-based items might help in screening depression.

Despite being very innovative, the above mentioned studies present some major limitations. First, they are conducted only with patients and the elderly. Hence they do not give any hints on the use of such tools among younger adults. Considering the increase of depression rates among youth and young adults (see Mojtabai et al., 2016), this is a relevant limitation. Moreover, they used only few (3 and 1 respectively) emoji, which could account for the lack of sensitivity of these tools. Therefore, more studies with young adults and with more sensitive tools are needed.

In the attempt to overcome the above mentioned limitations, we tested an emoji-based instrument to assess depression among normative young adults. Emoji cover a broad and ever-increasing range of areas and subjects and are used by 92 percent of the online population (EMOGI, 2015). They are increasingly employed, especially among young people, as a rapid, informal way to convey emotions (Walther and D'Addario, 2001) and attitudes (e.g., sarcasm, Dresner and Herring, 2010) in instant messaging (Statista, 2013), and social media (Dimson, 2015). Therefore, they have a great potential to reach and to be understood by young generations.

1.1. The present research

In order to develop a new brief emoji-based instrument to measure depression among young adults, we conducted two studies. In Study 1, we recruited a sample of young adults and investigated the association between rating on items presenting emoji as symptom descriptors and a validated measure of depressive symptoms, i.e., the 10-item short-form version of the Center for Epidemiologic Studies - Depression Scale (CESD-10, Andresen et al., 1994). Then, based on the strength of emerging associations, we selected a subset of the emoji items to create a brief screening tool.

In Study 2, we administered the emoji items selected in Study 1 to a new sample of respondents and investigated its reliability and construct validity, examining associations with depressive symptoms (i.e., CES-D 10) and Big Five traits, which were assessed using the Ten Item Personality Inventory (TIPI, Gosling et al., 2003). We expected to find a strong convergent validity between the new measure and a validated instrument to measure depression. Moreover, based on previous studies highlighting the existence of a stronger association of depression with neuroticism when compared with other Big Five traits (Bunevicius et al., 2008; Kendler, and Myers, 2010; Wood et al., 2010), we expected the emoji-based measure to show a moderate positive relation with neuroticism, and weaker relations with the openness, extraversion, agreeableness and consciousness traits. Finally, we developed a regression-based scoring procedure for the emoji items and tested its ability to detect individuals with clinically significant depressive symptoms.

2. Study 1

2.1. Method

2.1.1. Sample

Participants were recruited by publishing the link to an online research questionnaire on a range of social media platforms (i.e., Reddit, Facebook). Inclusion criteria were English language fluency, and age between 18 and 35. The link to the research was first disseminated online by a group of 10 university students. Data was collected from May to June 2017. Eventually, a total of 438 individuals provided either a partial (N = 8) or complete (N = 430) response to the questionnaire. Partial responses consisted of observations including only responses to the first section of the survey, i.e., demographic variables. The final study sample consisted of 430 individuals reporting no missing data on the questionnaire with mean age 24.99 (SD = 8.13), and 57.7% female, 38.9% males, and 3.5% indicating a non-binary gender identity. The majority of participants (80.2%) reported living in English-speaking countries (i.e., USA, UK, Canada, Australia, New Zealand), 13.4% lived in European countries, and ~7% lived in South American, Middle East, or Asian countries. Participants reported either college- (28.8%) or university-level education (43.5%), while 27.7% reported either high school or vocational-school education. As regards the operative system used by participants in their mobile devices, 45.8% indicated using Android, 48.8% uses Apple, 5.4% another operating system).

2.1.2. Measures

2.1.2.1. Emoji survey. The emoji included in the survey were extracted from one the earliest and most popular emoji font sets, the Apple Color Emoji font set, which includes more than 1600 emoji (for a complete list, see http://emojipedia.org/apple/) and is available in the popular Apple's iMessage and Facebook's Whatsapp instant messaging services. For the purpose of the present study, we selected 36 emoji (for the full list, see Table A1 in the supplementary material) that have previously shown significant associations with personality traits with theoretical and empirical links with emotion and affective processing (e.g., neuroticism and extraversion, Marengo et al., 2017). The selected emoji consists of 31 emoji representing stylised faces depicting different emotions (e.g., 😉, 😊,😢), while the remaining 5 emoji depict symbols (i.e.,❤️, 🎉) or gestures (i.e., 💪,✌️,👊). The 36 selected emoji were included in the questionnaire as items with the following common stem: "Below is a list of emoji depicting some of the ways you may have felt or behaved. Please indicate if each of the following was true for you much of the time during the past week." The items were scored as True (1) or False (0). In order to provide the same visual experience for individuals accessing the survey from devices using different operative systems (e.g., Android, iOS), the emoji were included in the survey as picture files depicting the emoji using the Apple Color Emoji rendering. All emoji were presented in the same page of the survey, as this approach is expected to results in lower administration time and missing responses (e.g., Mason and Huff, 2018). In order to mitigate potential bias related to presentation order effects, the item order was randomised at each online survey

administration.

2.1.2.2. Depressive symptoms. The CES-D 10 (Andresen et al., 1994) was used to assess participants' depressive symptoms. The CES-D 10 is a brief, widely used, self-report instrument for assessing depression over the past week. It consists of 10 items (e.g., "I felt depressed."; "I could not get going"; "I was happy" (reversed)) which can be rated on a 4-point scale from 0 (*less than one day*) to 3 (*5–7 days*). The CES-D 10 has demonstrated adequate internal consistency in this study (α = 0.78).

2.1.3. Strategy of analysis

First, for each emoji-based item, we computed the percentage of responses by response category (True/False). Next, for each emoji, we computed Pearson's correlation between emoji scores and CES-D 10 scores. Next, we examined the dataset to identify the most promising subset of emoji items for potential inclusion in a brief instrument for assessing depressive symptoms. More specifically, we aimed at identifying the set of emoji-based items with the strongest association with participants' CES-D 10 score while also minimising the redundancy of information. Selection was performed using a machine learning approach. More specifically, we employed the Correlation-based Feature Selection (CFS) algorithm by Hall (1998) and identified a subset of emoji items showing both the strongest predictive power over the CES-D 10 score. We used this strategy because it maximises overall predictive power while limiting the redundancy of information (Hall, 1998). Selection analyses were performed using *CfsSubsetEval* selection module as available in the WEKA software (Frank et al., 2016). Item selection was performed using an 80%−20% cross-validation procedure to prevent overfitting.

The convergent validity of the selected emoji set and the CES-D 10 score was evaluated by examining the disattenuated correlation between the total score computed on the emoji-based items the and CES-D 10 score.

2.2. Results

The emoji item reporting the highest percentage of participants experiencing it as a symptom in the previous week was 😂 (68% of True responses), while 🤫 was the least endorsed item (27% of True responses). Except for 😜, 👊, and 😱, all the emoji-based items showed significant correlations with the CESD-10 score. 😔 showed the strongest positive correlation with the CESD-10 score ($r = 0.49$, $p < .001$), while 😃 showed the strongest negative correlation ($r = -0.30$, $p < .001$). Descriptive statistics and correlation with CES-D 10 scores for the full emoji set are reported in the supplementary material (Table A1).

Results of the selection process indicated 10 items as the most promising set of predictors of the CES-D 10 score: 7 of the selected emoji express negative emotions (i.e., 😔,😞,😢,😖, 😣,😨,😟), and 3 expressed positive emotions (i.e.,😃,😄,😘). A total score for the items was computed by summing the item scores. Emoji-based items showing negative correlation with CESD-10 were reverse coded before computing the total score. Alpha computed on the item subset was acceptable (α = 0.71). After correcting it for attenuation due to measurement error, correlation between the emoji-based and CES-D 10 scores was 0.93, indicating strong convergent validity between the scores.

3. Study 2

3.1. Method

3.1.1. Sample

As for Study 1, we recruited participants by publishing the link to an online research questionnaire on a range of social media platforms (i.e., Reddit, Facebook), which was disseminated online by a group of 10 university students. Inclusion criteria were English language fluency, and age between 18 and 35. Data collection took place from August 2017 to October 2018. Eventually, 596 individuals accessed the online questionnaire and provided either a partial (N = 112) or complete (N = 482) response to the questionnaire. Partial responses consisted of individuals providing only answers to questions about demographic variables, but failing to answer the questions assessing the other study measures. For the purpose of this study, the sample consisted of 482 individuals providing full responses to the questionnaire, with a mean age of 25.01 (SD = 7.06), and 54.8% female, 40.9% males, and 4.3% indicating a non-binary gender identity. As in study 1, the majority of participants (83.1%) reported living English-speaking countries, while remaining individuals lived in European countries (12.4%), and South American, Middle East, or Asian countries (~4.5%). Participants reported either college- (31.7%) or university-level education (45.5%), while 22.8% reporting either high school or vocational-school education. Participants' use of mobile devices was also similar (50.0% Android, 45.4% iOS, 4.6% other).

3.1.2. Measures

3.1.2.1. Emoji survey. The administered items consisted of the 10 emoji selected in Study 1. Based on the classification of emotional valence reported in the Lisbon Emoji and Emoticon Database (Rodrigues et al., 2018), the selected emoji are expected to convey either negative (😔,😞,😢,😖, 😣,😨,😟) or positive (😃,😄,😘) emotions, and to show convergent interpretation across operative systems (e.g., Android, iOS). The emoji were presented using a common stem: "Below is a list of emoji depicting some of the ways you may have felt or behaved. Please indicate if each of the following was true for you much of the time during the past week." The items were scored as True (1) or False (0). As in Study 1, items were all presented in the same page, and item order was randomised at each administration.

3.1.2.2. Depressive symptoms. The CES-D 10 was used to assess participants' depressive symptoms (α = 0.86). A cut-off score of 10 was used to identify individuals showing clinically significant depressive symptoms (Andresen et al., 1994).

3.1.2.3. Big five personality traits. Personality differences were assessed by administering the TIPI questionnaire (Gosling et al., 2003), a short, validated measure assessing the Big-Five personality traits of extraversion, agreeableness, conscientiousness, emotional stability, and openness to new experiences. The instrument consists of 10 items (2 items per trait) with a common stem of 'I see myself as'. Each item is rated on a 7-point scale ranging from 1 (disagree strongly) to 7 (agree strongly). TIPI personality scales have shown good psychometric properties when compared with longer instruments assessing Big-Five personality traits. Given the low number of items, by design the scales are expected to show low reliability. For the present study, α ranged from 0.39 to 0.81.

3.1.3. Strategy of analysis

First, for each emoji-based item, we computed the percentage of responses by response category (True/False), and examined the correlations between each emoji and CES-D 10 score. Then, we investigated reliability for the selected set of items by computing Cronbach's alpha coefficient. Next, we computed a total score of emoji- based depressive symptoms scale by adding up the item scores. Emoji-based items showing negative correlation with CES-D 10 (i.e.,😃,😄,😘) were reverse coded prior to computing the total score. Reliability was investigated using Cronbach's Alpha. Construct validity of the emoji-based total score was investigated by examining disattenuated correlations between the emoji score, the CES-D 10 and TIPI personality scores.

Finally, we developed a regression-based scoring procedure for the emoji items aimed at improving its ability to identify individuals at risk for clinical depressive symptoms. We used a two-step procedure. As a

Table 1
Emoji items: Percentage of responses by category, and correlation with CESD-10 (N = 482).

		Item response		
Emoji	Unicode name	True	False	CES-D 10
	Smiling face with open mouth	69.71%	30.29%	−0.39***
	Smiling face with open mouth and smiling eyes	69.09%	30.91%	−0.40***
	Face throwing a kiss	55.60%	44.40%	−0.16***
	Pensive face	73.03%	26.97%	0.43***
	Disappointed face	66.80%	33.20%	0.39***
	Crying face	46.89%	53.11%	0.37***
	Confounded face	39.00%	61.00%	0.24***
	Persevering face	53.53%	46.47%	0.28***
	Fearful face	38.59%	61.41%	0.24***
	Worried face	52.90%	47.10%	0.24***

Note.
*** p < .001.

first step, we implemented a regression model using the emoji items as predictors of the CES-D 10 score, and used estimated coefficients to compute a weighted score for the emoji items. As a second step, we examined the ability of this newly obtained score to detected individuals at risk for clinically significant depressive symptoms. More specifically, we computed the area under curve (AUC) of the receiver operator characteristic (ROC), plotting the sensitivity, i.e. the probability that an individual is accurately identified as showing signs of clinically significant depression, versus specificity, i.e. the probability that individuals with no signs of depression are classified as showing no significant depressive symptoms, for all possible cut-off points of this newly obtained emoji-based score. Then we selected a threshold based on the maximal value of the Youden's J index, i.e., the point maximising both test sensitivity and specificity (Hajian-Tilaki, 2013).

3.2. Results

3.2.1. Reliability and construct validity

Table 1 shows the percentage of True/False responses for each emoji-based item, as well as the correlation between each emoji item and the CESD-10 scores. Correlations between emoji-based items and CESD-10 scores were all significant, and consistent with those observed in Study 1.

Cronbach's alpha computed on the selected item set was acceptable (α = 0.70). Correlations computed between the emoji-based sum score and the CES-D 10 and TIPI scores showed indications of both convergent and discriminant validity (see Table 2). Convergent validity was tested by computing the correlation between test score and depression scores as measured by CES-D 10. The emoji-based score showed a strong positive correlation with the CES-D 10 (r = 0.82, p < .01). Evidence of convergent validity also emerged as the TIPI Neuroticism scale was moderately related to the emoji-based score (r = 0.61, p < .01). The lower strength of correlations between the emoji-based score and extraversion (r = −0.31, p < .01), agreeableness (r = −0.27, p < .01), and openness scores (r = −0.21, p < .05), and conscientiousness (r = - 0.19, p < .05) provided support for discriminant evidence of validity. It is worthy to note that both the emoji-based score and the CES-D 10 showed a similar pattern of correlations with the Big Five Traits (see Table 2).

Table 2
Correlations between the emoji-based total score, the CES-D 10, and Big Five traits (N = 482).

	CES-D 10	EMOJI
CES-D 10	–	0.82***
Extraversion	−0.35***	−0.31***
Agreeableness	−0.29***	−0.27**
Conscientiousness	−0.36***	−0.19*
Neuroticism	0.66***	0.61***
Openness	−0.21*	−0.21*

Note.
* p < .05,.
** p < .01,.
*** p < .001.

3.2.2. Development of a screening procedure for depressive symptoms

As a final aim of the study, we developed a scoring procedure for the emoji items aimed at detecting individuals showing signs of clinically significant depressive symptoms. First, we tested a multiple linear regression model predicting the CES-D 10 score using the selected emoji as predictors. Then, based on results from the regression model (R^2 = 0.47), we produced a scoring equation in which items were weighted according to the estimated unstandardised regression coefficient representing their association with the CES-D 10 score, whose resulting variable we labelled the EMOJI-D:

EMOJI-D = 11.81 + (-2.87* 😃) + (-3.55* 😄) + (-0.98* 😘) + (3.73* 😔) +
+ (2.35* 😞) + (2.14* 😢) + (0.42* 😖) + (0.55* 😣) + (0.99* 😰) + (0.41* 😟)

Finally, we examined the use of the EMOJI-D to detect individuals showing clinically significant symptoms (CES-D 10 score > = 10). We computed the AUC of the ROC curve (see Fig. 1), and selected a threshold based on Youden's J index. ROC curve analysis results indicated that the EMOJI-D showed good accuracy in detecting

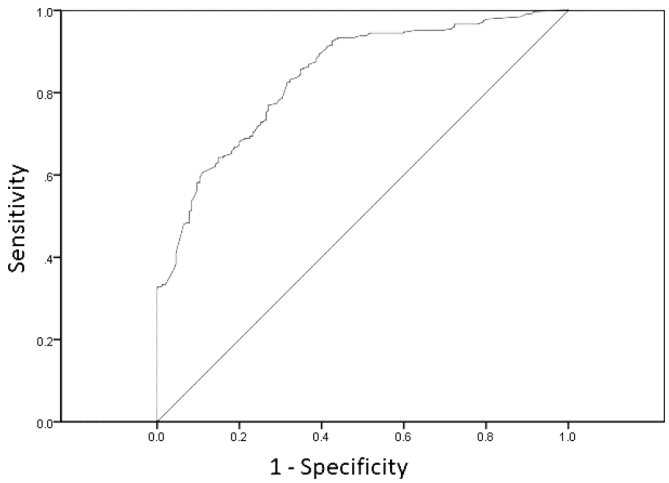

Fig. 1. Receiving operating characteristic curve for the EMOJI-D (CES-D 10 > = 10).

individuals showing signs of clinically significant depressive symptoms (AUC = 0.84, $p < .01$, 95% CI between 0.80 and 0.87). The maximal Youden's *J* statistic was 0.51, corresponding to EMOJI-D values > 11.80. Using this cut-point, the Emoji-D score showed a sensitivity of 82.57 and a specificity of 68.39.

4. Discussion

The aim of this study was to test a new emoji-based instrument to assess depression symptoms among young adults. Study 1 explored the associations between self-report depressive symptoms and participants' rating of emoji as symptom descriptors. Then, 10 emoji were selected for potential inclusion in a brief instrument for the assessment of depression. In Study 2, we found that this set of emoji showed a very strong relation with a well-known and validated measure of depression (CES-D 10). Moreover, similarly to CES-D 10, they showed a good convergent and divergent validity with different dimensions of personality. Finally, the new measure showed a good sensitivity and specificity in detecting individuals that present problematic levels of depressive symptoms with CES-D 10. All these results are very promising and suggest that an emoji-based instrument might be appropriate to individuate persons with elevated levels of depression symptoms.

The relation between the new emoji-based instrument and CES-D 10, which is a well-validated instrument to assess depressive symptoms, is quite impressive. Furthermore, it is important to notice that the selected emoji were mostly consistent with 2 facets, namely positive and negative affect, commonly emerging from factor analyses conducted on instruments to measure depression (for a review see Shafer, 2006), as well as studies exploring the emotional valence of emoji (e.g., Rodrigues et al., 2018). This is also consistent with previous studies exploring use of emoticons to measure depression in patient populations (Lee et al., 2008; Tan et al., 2018). However, when compared with these studies, it is worth noting that the present emoji-based instrument is more comprehensive and shows better specificity, which ensures its reliability in detecting problematic levels of depressive symptoms.

The emoji-based measure showed to have similar relations with other constructs as other text-based measures, such as CES-D 10. These relationships are consistent with the literature (e.g., Bunevicius et al., 2008; Kendler and Myers, 2010) and provide strong support for the construct validity of the emoji-based measure of depressive symptoms and for its ability to tap different aspects of the construct.

Concerning the accuracy of the emoji-based screening test for depression, our results are encouraging. The use of the emoji-based measure made it possible to detect individuals experiencing clinically relevant depressive symptoms with good sensitivity and fair specificity. Overall, the results from the present study appear to be in line with what was reported for a wide range of depression screening tests (Calonge et al., 2009), and suggest that the emoji-based questionnaire may be useful for screening purposes.

Our study has weaknesses. The main limitation consists in the adoption of an online snowball sampling procedure, a procedure that does not guarantee the representativeness of the sample. However, studies using this kind of sampling are especially suitable to reach young adults in the online environment (Bauermeister et al., 2012; Kosinski et al., 2015; Settanni et al., 2018). Still, samples of both studies show a slight prevalence of female participants, which may be linked to a self-selection bias possibly linked to the higher preference for emoji among female Internet users when compared to males (Chen et al., 2018). Future replications employing larger, more controlled samples could help strengthen the result of the study. Another limitation relates to the use of a binary response format to rate emoji items, a choice taken in order to limit the cognitive load required to answer the test and shorten administration time. However, this choice may have lowered the reliability of the assessment when compared with using more response options, e.g., a 4-point response scale. Future studies will permit to examine the influence of different response formats on the overall functioning of emoji items.

This study has strengths too. First, to our knowledge, this is the first study that demonstrates the ability of an emoji-based measure to assess depressive symptoms among normative young adults. This opens new perspectives on the screening of adults that suffer from depressive symptoms even without reaching the significance for a diagnosis. Second, we tested this measure with two different samples finding high convergent validity with similar results, and a remarkable level of accuracy in detecting individuals with depression problems. Therefore, our results seem to be very robust. Finally, some features of the test may help lower the barriers to depression screening among young adults, namely 1) low average administration time (~ 1 min), 2) use of a popular, easy-to-understand set of image-based items, minimising the cognitive effort required to read and answer the test, and 3) an assessment procedure that is mostly language-free. Because they have the potential to be understood even by individuals with low literacy skills, emoji items may be suitable for use even among older adults or children (e.g., Fane et al., 2018). In this view, the exploration of the use of emoji for depression assessment among older and younger samples represents a promising avenue for future research. Further, given the differential preference for emoji across age groups (e.g., Prada et al., 2018), future studies should investigate possible age-related differences in the functioning of emoji as depression indicators.

To conclude, emoji represent a new form of expression in the era of computer-mediated communication. They are becoming more and more common and popular among young adults, and because of their lack of verbal content, they are mostly language-independent. These characteristics, together with the results of the present study, make the emoji a powerful tool of screening for depression with the potential to reach increasingly large and diverse online populations.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.psychres.2019.02.059.

References

An, M., 2017. Content trends: preferences emerge along generational fault lines. Hubspot.com. Retrieved from: https://research.hubspot.com/content-trends-preferences.

Andresen, E.M., Malmgren, J.A., Carter, W.B., Patrick, D.L., 1994. Screening for depression in well older adults: evaluation of a short form of the CES-D. *Am. J. Prev. Med.* 10 (2), 77–84.

Bauermeister, J.A., Zimmerman, M.A., Johns, M.M., Glowacki, P., Stoddard, S., Volz, E., 2012. Innovative recruitment using online networks: lessons learned from an online study of alcohol and other drug use utilizing a web-based, respondent-driven sampling (webRDS) strategy. *J. Stud. Alcohol Drugs* 73 (5), 834–838.

Beck, A.T., Steer, R.A., Brown, G.K., 1996. Beck Depression Inventory-II (BDI-II). Psychological Corporation, San Antonio, TX.

Bunevicius, A., Katkute, A., Bunevicius, R., 2008. Symptoms of anxiety and depression in medical students and in humanities students: relationship with big-five personality dimensions and vulnerability to stress. *Int. J. Soc. Psychiatry* 54 (6), 494–501.

Calonge, N., Petitti, D.B., DeWitt, T.G., Dietrich, A.J., Gordis, L., Gregory, K.D., ..., Loveland-Cherry, C., 2009. Screening for depression in adults: US preventive services task force recommendation statement. *Ann. Intern. Med.* 151 (11), 784–792.

Chen, Z., Lu, X., Ai, W., Li, H., Mei, Q., Liu, X., 2018, April, April. Through a gender lens: learning usage patterns of emojis from large-scale android users. In: Proceedings of the 2018 World Wide Web Conference on World Wide Web (pp. 763-772). International World Wide Web Conferences Steering Committee.

Dimson, T., 2015. Emojineering part 1: machine learning for emoji trends [blog]. Retrieved from. http://instagram-engineering.tumblr.com/post/117889701472/emojineering-part-1-machine-learning-for-emoji/.

Dresner, E., Herring, S.C., 2010. Functions of the nonverbal in CMC: emoticons and illocutionary force. *Commun. Theory* 20 (3), 249–268.

EMOGI, 2015. In: Emoji report. Retrieved from. http://emogi.com/documents/Emoji_Report_2015.pdf.

Fane, J., MacDougall, C., Jovanovic, J., Redmond, G., Gibbs, L., 2018. Exploring the use of emoji as a visual research method for eliciting young children's voices in childhood research. *Early Child Develop. Care* 188 (3), 359–374.

Frank, E., Hall, M.A., Witten, I.H., 2016. The WEKA Workbench. Online Appendix for "Data Mining: Practical Machine Learning Tools and Techniques". Morgan Kaufmann Fourth Edition, 2016.

Gosling, S.D., Rentfrow, P.J., Swann Jr, W.B., 2003. A very brief measure of the big-five

personality domains. *J. Res. Personal.* 37 (6), 504–528.
Hajian-Tilaki, K., 2013. Receiver operating characteristic (ROC) curve analysis for medical diagnostic test evaluation. *Caspian J. Intern. Med.* 4 (2), 627.
Hall, M.A., 1998. Correlation-based Feature Subset Selection for Machine Learning. Hamilton, New Zealand.
Jones, R.N., Gallo, J.J., 2002. Education and sex differences in the mini-mental state examination: effects of differential item functioning. *J. Gerontol. Series B Psycholog. Sci. Soc. Sci.* 57 (6), P548–P558.
Kendler, K.S., Myers, J., 2010. The genetic and environmental relationship between major depression and the five-factor model of personality. *Psychol. Med.* 40 (5), 801–806.
Kosinski, M., Matz, S.C., Gosling, S.D., Popov, V., Stillwell, D., 2015. Facebook as a research tool for the social sciences: opportunities, challenges, ethical considerations, and practical guidelines. *Am. Psychol.* 70 (6), 543.
Lee, A.C.K., Tang, S.W., Yu, G.K.K., Cheung, R.T.F., 2008. The smiley as a simple screening tool for depression after stroke: a preliminary study. *Int. J. Nurs. Stud.* 45 (7), 1081–1089.
Marengo, D., Giannotta, F., Settanni, M., 2017. Assessing personality using emoji: an exploratory study. *Personal. Indiv. Diff.* 112, 74–78.
Marengo, D., Longobardi, C., Fabris, M.A., Settanni, M., 2018. Highly-visual social media and internalizing symptoms in adolescence: the mediating role of body image concerns. *Comput. Hum. Behav.* 82, 63–69.
Mason, R., Huff, K., 2018. The effect of format and device on the performance and usability of web-based questionnaires. *Int. J. Soc. Res. Methodol.* 1–10.
McCallum, R.S. (Ed.), 2003. Handbook of Nonverbal Assessment 30 Kluwer Academic/Plenum Publishers, New York, NY.
Mojtabai, R., Olfson, M., Han, B., 2016. National trends in the prevalence and treatment of depression in adolescents and young adults. *Pediatrics*, e20161878.
Mui, A.C., Burnette, D., Chen, L.M., 2001. Cross-cultural assessment of geriatric depression: a review of the CES-D and the GDS. *J. Mental Health Aging*.
Naglieri, J.A., 2003. Naglieri nonverbal ability tests. Handbook of Nonverbal Assessment. Springer, US, pp. 175–189.
Prada, M., Rodrigues, D.L., Garrido, M.V., Lopes, D., Cavalheiro, B., Gaspar, R., 2018. Motives, frequency and attitudes toward emoji and emoticon use. *Telemat. Inform.* 35 (7), 1925–1934.
Rammstedt, B., Goldberg, L.R., Borg, I., 2010. The measurement equivalence of Big-Five factor markers for persons with different levels of education. *J. Res. Personal.* 44 (1), 53–61.
Rodrigues, D., Prada, M., Gaspar, R., Garrido, M.V., Lopes, D., 2018. Lisbon Emoji and Emoticon Database (LEED): norms for emoji and emoticons in seven evaluative dimensions. *Behav. Res. Methods* 50 (1), 392–405.
Rolland, J.P., Parker, W.D., Stumpf, H., 1998. A psychometric examination of the French translations of NEO-PI-R and NEO-FFI. *J. Pers. Assess.* 71 (2), 269–291.
Settanni, M., Azucar, D., Marengo, D., 2018. Predicting individual characteristics from digital traces on social media: a meta-analysis. *Cyberpsychol. Behav. Soc. Netw.* 21 (4), 217–228.
Settanni, M., Marengo, D., 2015. Sharing feelings online: studying emotional well-being via automated text analysis of Facebook posts. *Front. Psychol.* 6, 1045.
Shafer, A.B., 2006. Metaanalysis of the factor structures of four depression questionnaires: beck, CES-D, Hamilton, and Zung. *J. Clin. Psychol.* 62 (1), 123–146.
Statista, 2013. Sticker and emoji usage in mobile messaging apps 2013. Retrieved from. http://www.statista.com/statistics/301061/mobile-messaging-apps-sticker-emoji-usage/.
Tan, L., Toh, H.J., Sim, L.K., Low, J.A., 2018. Sensitivity and specificity analysis: use of emoticon for screening of depression in elderly in Singapore. *J. Am. Psychiat. Nurses Assoc.*, 1078390318766665.
Teresi, J.A., Ramirez, M., Lai, J.S., Silver, S., 2008. Occurrences and sources of differential item functioning (DIF) in patient-reported outcome measures: description of DIF methods, and review of measures of depression, quality of life and general health. *Psychol. Sci. Quart.* 50 (4), 538.
Walther, J.B., D'Addario, K.P., 2001. The impacts of emoticons on message interpretation in computer-mediated communication. *Soc. Sci. Comp. Rev.* 19 (3), 324–347.
Wood, A.M., Taylor, P.J., Joseph, S., 2010. Does the CES-D measure a continuum from depression to happiness? Comparing substantive and artifactual models. *Psychiatry Res.* 177 (1–2), 120–123.