ORIGINAL ARTICLE

Development and Validation of the Mukbang Addiction Scale

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Abstract

Recent literature has speculated that some individuals spend lots of time watching mukbang (i.e., combination of the South Korean words 'eating' ['meokneun'] and 'broadcast' ['bangsong'] that refers to eating broadcasts where a person eats a large portion of food on camera whilst interacting with viewers) and compensate different needs using this activity. However, compensating unattained offline needs using a specific online activity could lead to the addictive use of that activity. The present study investigated problematic mukbang watching by developing and validating the Mukbang Addiction Scale (MAS). An online survey was administered to 236 university students (M_{age} = 20.50 years; 62% female) who had watched mukbang at least once. Construct validity, criterion validity, and reliability analyses indicated that the MAS had good psychometric properties. Exploratory and confirmatory factor analyses confirmed the unidimensional structure of the scale. The Cronbach's alpha (α = .95) and composite reliability (CR = .92) suggested that the MAS had excellent internal consistency. Latent class analyses (LCA) revealed two primary profiles, one with high endorsement and one with low endorsement of the items assessed. Item response theory (IRT) findings also indicated a good model fit. IRT findings provisionally supported a cut-off scale raw score of 22 (out of 30). Assessment and clinical-related implications of the findings are illustrated in accordance with other excessive behaviours.

Keywords Mukbang · Online eating · Problematic mukbang use · Mukbang addiction · Internet · Internet addiction

Recent newspaper coverage has indicated that there has been a growing phenomenon of individuals using internet applications for engaging in a relatively new online activity, watching mukbang (McCarthy 2017). Mukbang is a combination of the South Korean words 'eating' ('meokneun') and 'broadcast' ('bangsong'), and refers to online eating shows where a *mukbanger* or broadcast jockey (the individual in the broadcast) eats large portions of food on camera whilst interacting with viewers

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(McCarthy 2017). Mukbang started as live-stream eating shows on *Afreeca TV* in South Korea around 2008 and was introduced to western audiences on English language social media channels in 2014 (Donnar 2017). Mukbang has now become increasingly popular in different countries where hundreds of thousands of individuals watch mukbang every day by using different online applications (Hawthorne 2019).

Individuals appear to watch mukbang for different motivations. A recent study, analysing 67 mukbang video clips of a male South Korean mukbanger and the viewers' comments to these videos, claimed that individuals fulfilled their need to eat with company by feeling emotionally connected to mukbangers and other viewers (Choe 2019). Watching mukbang helped them to overcome loneliness and alienation by providing a sense of community. Some individuals watch mukbang in order to see young attractive women consume food (i.e., to provide some kind of sexual fantasy; Donnar 2017), whereas others simply seek entertainment (Choe 2019). It has also been reported that some viewers obtain pleasure from listening to eating and cooking sounds, resulting in a sense of happiness and relief (Woo 2018). Another qualitative study, interviewing three mukbangers, reported that mukbang watching functioned as an escape from unpleasant reality for individuals who were bored and/or felt stressed (Bruno and Chung 2017). Finally, it has been reported that individuals who are on a diet or are unable to access specific varieties of food watch mukbang in order to experience the vicarious satisfaction of binge eating of craved food via mukbangers (Bruno and Chung 2017; Donnar 2017; Gillespie 2019).

Several studies have concluded that mukbang watching might have negative consequences for the viewers including (i) increased consumption of food because of social comparison or mimicry, (ii) alteration of viewers' perception of food consumption and thinness, eating, health, table manners, and eating manners because of modelling of bad behaviours, and (iii) obesity and different eating disorders because of the glorification of binge eating (Bruno and Chung 2017; Donnar 2017; Hong and Park 2018; Park 2018; Shipman 2019; Spence et al. 2019). It has also been claimed that mukbang watching may also become addictive for a minority of people who use mukbang for social compensation (Malm 2014).

According to compensatory internet use model, compensating unattained offline needs using a specific online activity could lead to the development and maintenance of addictive use of that activity (Kardefelt-Winther 2014). For instance, compensating social needs by social media use and online gaming have been positively associated with both problematic social media use and online gaming addiction (Kircaburun, Alhabash, Tosuntaş, and Griffiths, 2018; Kuss and Griffiths 2012). Compensating real-life sexual needs in online contexts by having sexual fantasies could also lead to higher addictive use of online sexual activities (Wéry and Billieux 2016). Similarly, those who use social networking sites for entertainment report higher problematic social media use (Kircaburun et al. 2018). Furthermore, escapism is one of the key motivations that can facilitate some non-problematic activities such as gambling, gaming, and pornography use into problematic behaviours by creating positive mood modifying experiences (Király et al. 2015; Kor et al. 2014; Wood and Griffiths 2007).

From the compensatory internet use model perspective (Kardefelt-Winther 2014), it is hypothesised that some individuals could become problematic mukbang viewers because mukbang facilitates the compensation of different offline needs including social interaction, sexual fantasy, entertainment, escape from reality, and vicarious eating (Bruno and Chung, 2017; Choe 2019; Donnar 2017). Consequently, the present study focused on the possible addictive aspect of mukbang watching.

In order for problematic (in this case, addictive) mukbang watching to be examined, valid and reliable psychometric tools that can be used to assess problematic mukbang watching are

needed. To the best of authors' knowledge, no previous study has examined problematic mukbang watching and this may be because there are no assessment tools validated to assess problematic mukbang watching. Based on the aforementioned rationale, the present study developed the Mukbang Addiction Scale (MAS) by conducting a psychometric validation. For this purpose, the previously validated Bergen Facebook Addiction Scale (BFAS) (Andreassen et al. 2012) was modified by replacing the word 'Facebook' with 'mukbang watching'. Additionally, the optimum number of profiles that best describe problematic mukbang watching was identified. Finally, item and scale psychometric properties (e.g., difficulty, discrimination, reliability, and pseudoguessing), as well as the scale's optimum cut-off point, were determined (utilizing item response theory analysis [IRT]; Ágoston et al. 2018).

The BFAS was chosen because it assesses a behaviour within social media platforms (like mukbang watching), has been widely used, and has been validated in several languages (Andreassen et al. 2013; Phanasathit et al. 2015; Pontes et al. 2016; Wang et al. 2015; Yurdagül et al. 2019). The BFAS was also used to develop the MAS because of its brevity and sound theoretical basis that reflects core components of behavioural addiction (Griffiths 2005), which presumes that behavioural addictions are a biopsychosocial phenomenon comprising six core components: salience, mood modification, tolerance, withdrawal symptoms, conflict, and relapse (Griffiths 2005).

Methods

Participants and Procedure

Participants were undergraduate student mukbang viewers who completed an online survey. The survey was promoted on different online courses of a Turkish university's distance learning centre. Students were informed that participation in the study was anonymous and voluntary, and would not affect their grades. A total of 236 mukbang viewers whose ages ranged between 18 and 27 years ($M_{age} = 20.50$ years, $SD_{age} = 1.62$; 62% female) participated in the study (see Table 1 for full list of participant variables). The minimum sampling error of a population consisting 236 participants at the 95% confidence interval ($z = 1.96$) was ± 6.38. Ethical approval for the study was taken from the research team's university's ethics committee and complied with Helsinki declaration. No compensation (e.g. money, vouchers, and course credit) was provided for participation.

Measures

Demograhics and Mukbang Usage Participants' demographic characteristics relating to their gender, age, grade level, faculty, height, weight, and daily frequency of mukbang watching were asked in the survey.

Mukbang Addiction Scale The MAS (see Table 2) was developed by replacing the word 'Facebook' with 'mukbang watching' in the Turkish form (Tosuntas et al. 2019) of the Bergen Facebook Addiction Scale (Andreassen et al. 2012). The MAS comprises six items (e.g., "How often in the past year have you spent a lot of time thinking about mukbang or planned watching mukbang?") on a 5-point Likert scale from "very rarely" to "very often" that assess six components of addiction (i.e., salience, conflict, withdrawal, mood modification, tolerance, and relapse) outlined in the biopsychosocial framework of addiction (Griffiths 2005).

Table 1 Participants' demographic characteristics and frequency of mukbang watching

Variable	N	%
Gender		
Males	89	37.7
Females	147	62.3
Grade		
1	29	12.3
2	148	62.7
3	45	19.1
4	14	5.9
Faculty		
Economics and administrative sciences	26	11
Communication	18	7.6
Humanities and social sciences	22	9.3
Business administration	14	5.9
Vocational school	34	14.4
Architecture	41	17.4
Engineering	55	23.3
Body mass index		
Underweight	43	18.2
Normal weight	139	58.9
Overweight	45	19.1
Obese	8	3.4
Extremely obese	1	0.4
Frequency of daily use		
No daily use	102	43.2
0–1 h	99	41.9
1–2 h	19	8.1
2–3 h	6	2.5
3–4 h	4	1.7
More than 4 h	6	2.5

Statistical Analysis

All statistical analyses were carried out using SPSS 23, AMOS 23, and Mplus 7 software. First, frequency and descriptive statistics were computed with regard to gender, age, faculty, body mass index, and frequency of mukbang watching. Second, construct validity of the MAS was assessed using exploratory factor analysis (EFA) and confirmatory factor analysis (CFA).

Table 2 MAS items and their mean scores, standard deviations, and communalities

How often during the last year have you…	Mean (S.D.)	Communalities
Item 1. Spent a lot of time thinking about watching mukbang or planned watching mukbang?	1.54 (.92)	.72
Item 2. Felt an urge to watch mukbang more and more?	1.54 (.93)	.77
Item 3. Watched mukbang in order to forget about personal problems?	1.59 (.97)	.80
Item 4. Tried to cut down on the mukbang watching without success?	1.45 (.90)	.85
Item 5. Become restless or troubled if you have been prohibited from watching mukbang?	1.53 (1.01)	.75
Item 6. Watched mukbang so much that it has had a negative impact on your job/studies?	1.43 (.89)	.87

Third, criterion validity was assessed using structural equation modeling. These analyses were carried out with 5000 bootstrapped samples and 95% bias-corrected confidence intervals which addressed the risk of potential deviations from normality. In order to determine goodness of fit, root mean square residuals (RMSEA), standardised root mean square residuals (SRMR), comparative fit index (CFI), and goodness of fit index (GFI) were checked. According to Hu and Bentler (1999), RMSEA and SRMR lower than .05 indicate good fit and RMSEA and SRMR lower than .08 suggest adequate fit; CFI and GFI higher than .95 are good and CFI and GFI higher than .90 are acceptable.

Fourth, latent class analysis (LCA) was employed using Mplus software (Muthén and Muthén 2019) to identify potential problematic mukbang watching profiles. The means and variances of the classes/profiles across the specific items, as well as their scale means, were calculated based on the maximum likelihood with robust standard errors estimator (MLR; Li 2016). Models with progressively increasing number of classes/profiles were examined and their fit was compared based on the combination of the following fit indices: (i) Akaike Information Criterion (AIC; Vrieze 2012); (ii) Bayesian Information Criterion (BIC; Vrieze 2012); (iii) Vuong-Lo-Mendell-Rubin test (VLMR-LRT; Jung and Wickrama 2008); and entropy (index of classification accuracy; Celeux and Soromenho 1996).

Next, the psychometric properties of the scale, as a whole, and its independent items were assessed with the application of graded 3-PL item response theory (IRT) analyses (Embretson and Reise 2013). In general, IRT supports the notion that there is a measureable association between responses to an item and the latent factor (in the present case 'problematic mukbang watching'; Embretson and Reise 2013). Out of the various IRT models available, the unidimensional (based on the single dimension/factor assumed) graded three-parameter logistic model (3PLM; Embretson and Reise 2013) was selected. IRT also provides reliability measures for the scale as a whole (Test Information Function; TIF), as well as at the item level (Item Information Function; IIF), for every different level of the latent trait present, whilst accounting for the varying levels of items' difficulty. Finally, the IRT analysis evaluated local independence, which implies that the associations between items are attributed exclusively to the underpinning factor assessed (i.e., problematic mukbang watching).

Results

Descriptive Statistics

Frequencies and ratios of daily mukbang watching and demographic characteristics of participants are presented in Table 1. Students from 12 different faculties participated in this study. Among them, the top five faculties represented were as follows (from highest to lowest respectively): engineering (23%), architecture (17%), vocational school (14%), economics and administrative sciences (11%), and humanities and social sciences (9%). Moreover, 12% of the participants were freshmen, 63% were sophomore, and 19% were third-year students. Participants' body mass index (BMI) was calculated using their height and weight information. According to the categorisation made by the National Heart, Lung, and Blood Institute (Pi-Sunyer et al. 1998), 18% of the participants were underweight, 59% were normal weight, 19% were overweight, and 4% were obese. With regard to frequency of daily mukbang watching, 42% of the participants indicated watching mukbang less than 1 h daily, 8% between 1 and 1 h 59 min, 3% between 2 and 2 h 59 min, 2% between 3 and 3 h 59 min, and 2% 4 or more hours.

Construct Validity

First, EFA was computed to examine the factor structure of the MAS. KMO and Bartlett's test indicated that Kaiser-Meyer-Olkin measure of sampling adequacy was higher than .70 and Bartlett's test of sphericity was significant (Kline 2014), indicating a good structure (.87; $p < .001$). Initial eigenvalues showed that an extracted one-factor solution explained 79.45% of the variance which was above the threshold (Kline 2014). Extracted communalities of the items ranged between .72 (Item 1) and .87 (Item 6), showing that all items have high loads in the scale (Table 2), given that loadings above .50 are acceptable (Kline 2014). Next, CFA was used to confirm the obtained factor structure in EFA. Goodness of fit indices indicated mostly good fit to the data (χ^2/df = 2.42, RMSEA = .08 [CI 90% (.03, .13)], SRMR = .01, CFI = .99, GFI = .98). Standardised regression weights ranged between .74 (Item 1) and .95 (Item 6), and squared multiple correlations were between .54 and .90, which suggested all items had significant role in the scale. The results regarding EFA (communalities produced) and CFA (standardised regression weights) of the MAS are presented in Table 2 and Fig. 1 respectively. These results indicated that the MAS had good construct validity and can be used to assess Turkish individuals' problematic mukbang watching.

Criterion Validity

The present study assessed criterion validity using a well-accepted gold standard indicator of the MAS (Bryant et al. 2007). Frequency of daily use of a specific application (e.g., social media) has been shown to be the most consistent indicator of addictive use of that particular application (Griffiths et al. 2014). Therefore, frequency of daily mukbang watching was included into structural equation modeling (SEM) as a predictor of problematic mukbang watching assessed by MAS. The results indicated mostly good fit to the data (χ^2/df = 2.20, RMSEA = .07 [CI 90% (.03, .13)], SRMR = .02, CFI = .99, GFI = .97). The model explained 18% of the variance in problematic mukbang watching ($\beta = .42$, $p < .001$ CI 95% [.26, .58]).
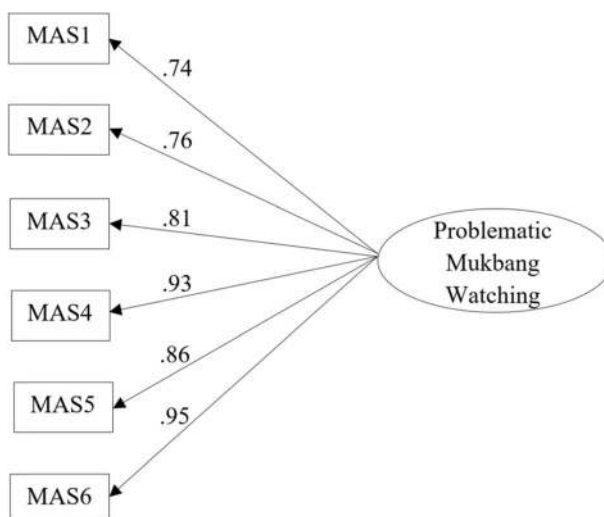

Fig. 1 Summary of confirmatory factor analysis of the MAS

The correlation coefficient between frequency of daily mukbang watching and problematic mukbang watching provided further support for MAS' criterion validity ($r = .42$, $p < .001$ CI 95% [.27, .56]).

Reliability Analysis

The reliability coefficient, Cronbach's alpha, of MAS was very high ($\alpha = .95$) and inter-item correlations were also high ($> .50$). Furthermore, the composite reliability of the scale (CR = .92) was above the accepted threshold of .70 (Fornell and Larcker 1981). These results demonstrate that the MAS appears to have good internal consistency.

Latent Class Analysis

The assessment of a two-class model supported a Vuong-Lo-Mendell-Rubin test (VLMR-LRT; H0 Loglikelihood Value) of − 1249.98, a 2-Time loglikelihood difference of 1324.11 and a p value of .017 proposing that a model of three profiles should be additionally examined. The bootstrapped parametric likelihood ratio VLMR-LRT (1290.37; $p = .0186$), which enhances the robustness of the analysis (Muthén and Muthén 2019) further supported this finding. A three-class model was evaluated, resulting in a non-significant VLMR-LRT value (269.45; $p = .2669$). Therefore, it was concluded that two profiles were satisfactory and that the addition of one more profile was unnecessary. The model fit for the two-class model related to an AIC of 2537.96, a BIC of 2603.77, and a sample-size adjusted BIC of 2543.55, which were lower than the alternatively tested one-class model, and therefore indicating a better fit. The final class counts and proportions for the two classes/profiles based on the optimum model tested, as well as their estimated posterior probabilities suggested that 81% of participants were identified in Class 1, whilst 19% of participants were identified as Class 2. Considering the classification accuracy, the entropy rate for the two-class structure was .996, being situated very close to 1. This finding indicated a 99.6% probability of participants having been correctly classified.

In relation to the two classes, Class 1 item responses rated within the range of half a standard deviation (below the sample's averages) across all the items. This class was named the 'low endorsement' class. Similarly, the items' means of participants allocated in Class 2 ranged (consistently across items) between one and a half and two standard deviations above the sample's mean. This class was named the 'high endorsement' class. The mean difference between the two profiles was elevated for the criteria representing withdrawal and relapse (see Fig. 2).

IRT Psychometric Properties per Item and Scale

Table 3 presents the percentages per Likert point/threshold across the six scale items in relation to the low and high endorsement classes identified by the LCA. Considering local independence, the standardised LDχ^2 statistic across all the possible combination of two items calculated by IRTPRO ranged from 2.6 (for the pair of 'relapse' and 'withdrawal') to 9.2 (for the pair of 'conflict' and 'salience'; rates greater than 10 reflect local dependence; Cai et al. 2011). This result supports the assumption of local independence for all six criteria modeled in the 3PLM (therefore, no other latent factor-dimension was assumed to interfere). Considering the model fit, Table 4 describes the IRTPRO calculated S-χ^2 item-fit indices. According to
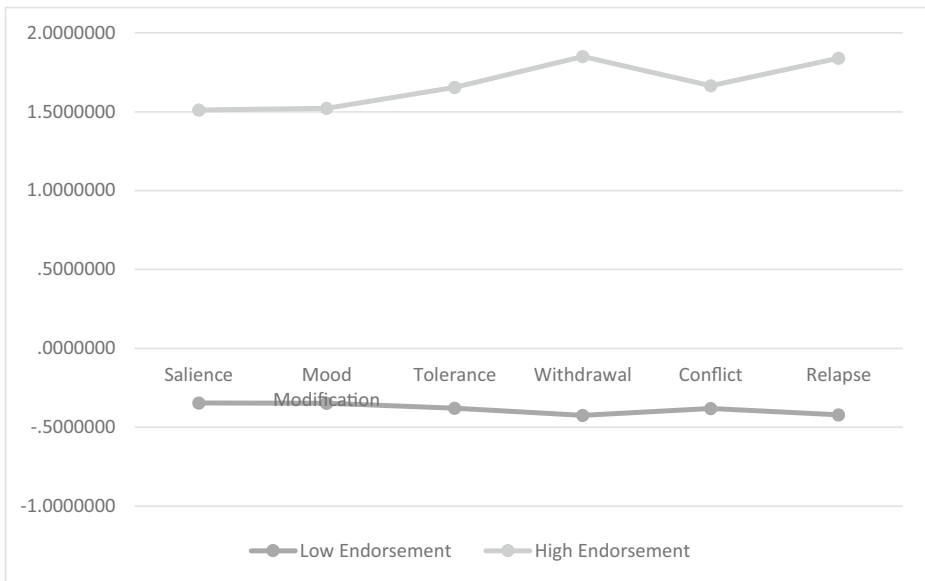
Fig. 2 The distribution of low and high endorsement classes across the six criteria

these, all six items had satisfactory fit (*p*-values ranged higher than 0.1). Considering the fit of the whole scale, the M_2 was also non-significant at $p = .01$ (M_2 [234] = 899.92, $p = .0177$), indicating an acceptable fit.

Pseudoguessing parameters followed complimentary patterns between the first and the last threshold across the six items, complimenting the item difficulty findings. Conclusively, these results indicate that (i) whilst increasing item scores correctly describe increasing levels of problematic mukbang watching across all items, the rate of these increases is different across the criteria, and (ii) different thresholds perform differently across items considering their level of difficulty, and therefore should be addressed differently by populations presenting with different levels of the problematic mukbang watching.

The trait of problematic mukbang watching inclined steeply, as the total score reported increased from 1 to 24. This proposes that the scale as a whole provides a sufficient

Table 3 Likert scale thresholds percentage across the sample

		1	2	3	4	5
Salience	Low endorsement	97.50%	86.70%	14.70%	16.70%	33.30%
	High endorsement	2.50%	13.30%	85.30%	83.30%	66.70%
Mood modification	Low endorsement	98.80%	72.40%	18.20%	42.90%	0%
	High endorsement	1.20%	27.60%	81.80%	57.10%	100%
Tolerance	Low endorsement	100%	88%	18.40%	11.10%	33.30%
	High endorsement	0%	12%	81.60%	88.90%	66.70%
Withdrawal	Low endorsement	99.40%	68.80%	3.30%	0%	0%
	High endorsement	0.60%	31.30%	96.70%	100%	100%
Conflict	Low endorsement	98.30%	87.50%	10.00%	12.50%	16.70%
	High endorsement	1.70%	12.50%	90.00%	87.50%	83.30%
Relapse	Low endorsement	98.90%	68.80%	0%	0%	0%
	High endorsement	1.10%	31.30%	100%	100%	100%

Table 4 Three-parameter logistic item response model parameter estimates and S-χ^2 indices

Item	Criterion	α	$\beta1$ (1–2)	C (1–2)	$\beta2$ (2–3)	C (2–3)	$\beta3$ (3–4)	C (3–4)	$\beta4$ (4–5)	C (4–5)	λ (loadings)	S-χ^2	df	p
1	Salience	4.12	0.45	− 1.84	0.89	− 3.69	1.66	− 6.83	2.03	− 8.35	0.92	37.27	16	0.200
2	Mood modification	4.47	0.47	− 2.1	0.91	− 4.05	1.54	− 6.86	1.94	− 8.66	0.93	39.09	15	0.100
3	Tolerance	4.97	0.42	− 2.08	0.78	− 3.89	1.5	− 7.44	1.95	− 9.68	0.95	36.55	16	0.200
4	Withdrawal	10.94	0.66	− 7.2	0.9	− 9.89	1.43	− 15.65	1.72	− 18.8	0.99	15.13	6	0.190
5	Conflict	5.95	0.62	− 3.67	0.87	− 5.16	1.39	− 8.26	1.65	− 9.83	0.96	42.49	17	0.100
6	Relapse	19.03	0.68	− 13.03	0.92	− 17.58	1.41	− 26.85	1.69	− 32.18	0.99	15.91	6	0.140

psychometric measure for assessing individuals with high and low levels of the problematic mukbang watching. The problematic mukbang watching level of two SDs above the mean trait level corresponds with a raw score of 22, and based on this, it is suggested as a conditional (before clinical assessment confirmation) diagnostic cut-off point. Considering the information provided by the scale as a whole, improved information were around 0 up to about + two SDs from the mean, with the exception of a significant drop around 1.2 SDs above the mean.

Discussion

The present study conducted a psychometric validation of the MAS including its construct validity, criterian validity, and reliability. The results indicated that the MAS has good validity and reliability for assessing problematic mukbang watching among Turkish participants. Developments in internet technologies have facilitated a variety of online behaviours into individuals' lives (e.g., shopping, gaming, gambling, sex, and social networking), leading to many different forms of gratifications obtained from these activities (Kircaburun et al. 2018). An emerging activity of watching others eat online (i.e., mukbang) has been argued to facilitate social, sexual, entertainment, escape, and eating uses for some individuals (Bruno and Chung 2017; Choe 2019; Donnar 2017; Gillespie 2019; Woo 2018). Obtaining these gratifications and constant reinforcements, watching mukbang has the potential to transform recreational viewing of mukbang into problematic mukbang watching based on studies examining other behavioural addictions (Király et al. 2015; Kircaburun et al. 2018; Kor et al. 2014; Wood and Griffiths 2007). Due to the lack of assessment, there is a need for a psychometrically valid and reliable assessment instrument for assessing mukbang watching.

Parallel to the aims of the present study, construct validity was tested using EFA and CFA. The extracted one-factor solution explained 79.45% of the variance and extracted communalities were between .72 and .87, indicating that all items had high contributions (Kline 2014). The CFA provided further empirical support the unidimensional structure with adequate to good fit indices (Hu and Bentler 1999). All item loadings in the final form were above .72 and significant. Despite its one-factor structure, as pointed out by Andreassen et al. (2012), MAS represents the six key components of addiction (i.e., tolerance, mood modification, withdrawal symptoms, salience, relapse, and conflict) outlined in the biopsychosocial framework of addiction (Griffiths 2005).

In order to investigate the criterion validity of the new scale, the direct effect of daily mukbang watching frequency on MAS was calculated using a structural equation model. Even though there was no empirical evidence regarding the relationship between the former and latter, extant behavioural addictions literature suggests that frequency of use of a specific online activity (e.g., social networking) is one of the most consistent indicators of addictive use of that activity (Griffiths et al. 2014). As expected, frequency of daily mukbang watching was positively (moderately) associated with problematic mukbang watching.

The reliability coefficient of the present scale was very high (.95) and inter-item correlations were also high (> .50). Moreover, the composite reliability of the scale was also very high (.92). These coefficient values were higher than some of the reported reliability of BFAS in previous studies (Andreassen et al. 2012, 2016; Pontes et al. 2016), providing indirect support for the internal consistency of the MAS.

Participants had the highest score on the item that assessed mood modification (i.e., watching mukbang in order to forget about personal problems). This result contradicts the

previous studies that validated the BFAS, which reported symptoms of salience (e.g., spending a lot of time thinking about Facebook or planned use of Facebook) and tolerance (e.g., feeling an urge to use Facebook more and more) as having the highest mean scores for Facebook use (Andreassen et al. 2012). Although using Facebook and watching mukbang are both activities carried out in social media, they differ in structure and content and this may explain why some addiction components differed in importance between the two activities. The item that assessed conflict (e.g., watching mukbang so much that it has had a negative impact on job/studies) had the lowest score among the six addiction components. This finding likely indicates that for most participants, mukbang watching had low negative consequences on their lives.

Considering the potentially applicable profiles, LCA revealed two distinct problematic mukbang watching groups, differing consistently in a quantitative manner across all the six items. Consequentially, these groups were defined as the 'low endorsement' and the 'high endorsement' classes, accounting for approximately 81% and 19% of the participants assessed respectively. Disordered mukbang watching behaviours were significantly lower for the first profile, whilst the difference between the two populations elevated in relation to the 'withdrawal' and the 'relapse' criteria. The existence of distinct profiles concerning the behaviour aligns with findings suggesting different profiles across addictive behaviours in general (Deleuze et al. 2015). Nevertheless, it should be noted that the participants classified in the 'high endorsement' class are high-risk individuals rather than addicted.

IRT findings confirmed the unidimensionality of the behaviour and indicated variations considering the discrimination, difficulty, and information functions of the items across the different thresholds taking into consideration the different levels of the underlying behaviour. More specifically, the descending succession of the items' discrimination power was 'relapse', 'withdrawal', 'conflict', 'tolerance', 'mood modification', and 'salience'. This corresponds with past IRT studies examining different forms of excessive behaviours that also advocated different discrimination power across the criteria assessed (Gomez et al. 2019).

Analyses suggested that different items should be interpreted with different clinical importance when it comes to assessment of this potentially problematic behaviour (whilst taking into consideration the level of the behaviour exhibited). Furthermore, findings showed that whilst all the items tended to provide better information between the mean and two SDs above the mean, the level of information tended to be significantly better for 'withdrawal' and (even more for) 'relapse', with the exception of a small area around one SD above the mean. The same trend was supported by the scale as a whole. In relation to the scale as a whole, problematic mukbang watching inclined steeply as the total score reported tended to elevate. This suggests the scale as a sufficient psychometric measure for assessing individuals with high and low levels of the problematic mukbang watching. Finally, given that a raw score of 22 corresponds two SDs above the mean of the latent factor, because this was assessed with the 3PL IRT graded model, this score could be provisionally considered as the scale's cut-off point (before further clinical assessment confirmation is considered).

There are several limitations that should be taken into consideration when interpreting the results of the present study. The study sample comprised mukbang viewers from a single Turkish university. Therefore, the present findings should be replicated using different samples from different countries and age groups. Second, the present study collected the data using a self-report online survey, which is susceptible to specific biases (e.g., social desirability, random responses, and memory recall). Therefore, future studies should adopt more in-depth methods to investigate problematic mukbang watching (e.g., qualitative interviews and focus groups). Third, the present study was a cross-sectional which restricts making any causal

assumptions. Therefore, future studies should use longitudinal studies to investigate possible bidirectional relationships regarding problematic mukbang watching. Nevertheless, the present study is the first to develop a psychometrically valid and reliable tool to assess those at risk of problematic mukbang watching, and can be used to assess problematic mukbang watching among Turkish emerging adults. This research provides a valuable contribution to the investigation of a growing phenomenon by validating an assessment tool that could be used to assess problematic mukbang use.

Compliance with Ethical Standards

Conflict of Interest   The authors declare that they have no conflict of interest.

Ethics   The study conducted with the approval of the research team's university ethics committee.

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