Hindawi
Human Behavior and Emerging Technologies
Volume 2023, Article ID 2363112, 11 pages
https://doi.org/10.1155/2023/2363112

Research Article

Italian Validation of the Social Media Engagement Questionnaire (SME-Q): A Preregistered Study

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Received 27 January 2023; Revised 18 May 2023; Accepted 28 July 2023; Published 11 August 2023

Academic Editor: Pinaki Chakraborty

The use of social media has frequently been misunderstood. Scholars worldwide have attempted to investigate patterns in social media use, with several attempts to frame it as a problematic behavior linked to negative consequences. However, among the different attempts, SME-Q has focused on the use *per se* during critical moments of the day, i.e., around bedtime and during meals. While the use of social media is a behavior adopted by a huge percentage of the population, several differences among countries can be detected that may lead to a different scale dimensionality. As such, in this paper, we translate and validate the Italian version of the SME-Q in order to provide a tool to explore social media use among the Italian population. The study involved 520 people through the compilation of an online survey aimed at investigating psychological and behavioral variables related to social media use which also included three attention checks to control for response biases due to inattention. The study outline, data collection, and analysis plans were preregistered and deposited on the project's website on the Open Science Framework. The results indicated a novel two-factor structure of the four-item scale with adequate values, revolving around a sleep time factor and a meal factor. The hypothesized relationships with the external validation variables have been confirmed. The successfully validated Italian SME-Q thus allows the exploration of social media engagement with the Italian-speaking population.

1. Introduction

DataReportal [1] detected a total of 4.65 billion social media (SM) users worldwide in April 2022, which corresponds to 58.7% of the total world population, thus highlighting a massive and widespread use of SM. In 2021, the number of SM users experienced a strong growth, with around 409 million new users joining these tools, representing an annual increase of 10.1%. By comparison, the annual increase in 2019, before the start of the COVID-19 pandemic, was only 7.2%, and in 2020, after the start of the pandemic, it was 13.2%, indicating a continued acceleration in the spread of SM use. To give a measure of typical SM use, the average user actively visits about seven different platforms each month and spends about 2 h, 29 m using SM each day, an annual increase of 7 minutes.

The already growing trend in the use of social media has experienced a further acceleration due to the particular context created by the pandemic [2]. The spread of social media during the COVID-19 pandemic was characterized by a general increase in the use of these tools among the population and by different types of use, including information search, distance learning, remote monitoring, and health care [3–6]. They have also been used with a social support search strategy to compensate for a sense of increased loneliness during the pandemic period [7–9].

Given the massive and pervasive use of social media in our current society, the scientific community has become interested in studying how people approach social media. Therefore, several constructs and measures have been developed by scholars [10–13]. For instance, "social media use" has been referred to as an umbrella term for indicating people's engagement with social media in terms of frequency, duration, intensity, and addiction [12].

There are two theoretical strands that define social media engagement in the literature: the business strand that operationalizes and conceives the engagement as actions within a social media [14, 15] and another strand [11, 16] which instead focuses on pervasive access and usage activity. Frequency of social media use was described as daily use frequency of each social platform or its function (e.g., number of likes and reposts). A representative instrument is the social media use scale developed by Rogers and Barber [13]. Duration of social media use measures the amount of time spent using social media on a daily or weekly basis. A representative instrument in this category is the Facebook usage scale developed by Buglass et al. [10]. However, analyzing activities on social media based just on "objective measures" (i.e., frequency of access, screen time) has not been found to adequately predict psychological outcomes [17–21]. Similarly, the reduction of social media use to just dysfunctional, problematic, and addiction-related dynamics makes it impossible to really capture the effects that a higher engagement with social media entails [22–24]. Indeed, social media use can be functional and has been found to contribute to people's well-being by addressing users' personal needs in many ways, including social support seeking and receiving positive feedback [25–27].

For this reason, the intensity scales developed in recent years have aimed at identifying general patterns of social media use, avoiding a specific focus on symptoms of social media addiction [12], but rather on any negative effects imposed on interpersonal [28, 29] and personal [30–32] levels by the intrusive and/or engaging use of technology.

The intensity scales of social media use assess the individual's emotional connection to social media or the integration of social media into their lives (e.g., Facebook Intensity Scale, [11]; Social Media Use Integration Scale (SMUIS); [33]).

Based on this framework, the Social Media Engagement Questionnaire (SME-Q, [16]) was developed to measure the extent to which participants use social media in their daily lives (i.e., behavioral engagement) referring to key moments of the day (i.e., around the time of waking up and falling asleep and during meals). In these key moments of the day, it is possible to identify a social component during meals, which is more related to technoference [28, 34] and phubbing behavior [35–37], and a more personal component, which is related to overnight use before going to sleep and use when waking up in the morning, without excluding the fact that a person can also have real-life social interactions in these circumstances.

Specifically, smartphone use during meals has often been associated with the phenomenon of phubbing (i.e., "phone snubbing": using the phone in social situations instead of interacting with people). Phubbing had significant consequences for social health, relationship health, and self-fulfillment and was significantly associated with depression and distress [35–39]. Meanwhile, smartphone use around bedtime has also been identified as problematic [40]. The use of smartphones or other electronic devices just before bedtime determines a number of biological effects, including increased arousal and a delay in circadian rhythms, which can perpetuate sleep deprivation, problematic sleep patterns, and reduced alertness the next morning [31, 32, 41]. Similarly, social media use near bedtime has been associated with reduced sleep quality, problematic sleep patterns, and negative mental health among adolescents and college students [30, 42, 43].

The SME-Q represents the gold standard of social media engagement measures as it captures both aspects (personal and interpersonal) of social media engagement without assuming this engagement to be problematic. For this reason, SME-Q differs from addiction scales (for example, BSMAS, [44]) because it does not refer to any theoretical model or clinical definition of addiction (e.g., Griffiths' addiction model; [45]) nor does it measure typical indicators of social media addiction (e.g., mood modification, salience). Correlations between SME-Q and measures of social media addiction exist but are not particularly high [46–48] if we consider the two measures as expression of the same construct (only about the 25% of variance is shared) [49], suggesting the alternative hypothesis that engagement and addiction are, actually, different constructs.

While some measures [11, 33] between social media intensity or engagement scales also capture the emotional dimension, other scales such as the SME-Q by Przybylski et al. [16] specifically capture the integration of SM use into daily life by focusing only on behavioral engagement. Other scales are specific to some contexts, such as the SMES [50], which examines SM engagement during class, while the SME-Q can be applied to any context due to its generality.

1.1. Worldwide Differences in Social Media Use and the Italian Case. SME-Q results are obtained in English-speaking countries, and thus, making generalizations to non-English speaking countries should be considered a violation of external validity, since people from different countries might adopt different approaches to SM. Indeed, according to DataReportal [1], among English-speaking countries, United Kingdom SM users in 2022 accounted for 84.3% of the total population (57.6 M of 68.35 M) while USA users accounted for 80.9% of the total population (270.1 M of 333.9 M) and Australia users for 82.7% of total population (21.45 M of 25.93 M). The percentage of SM users in non-English speaking European countries varies mildly, highlighting in all cases a widespread behavior: in Germany, SM users were 86.5% of the total population (72.6 M of 83.89 M); in France, they accounted for 80.3% of the total population (52.6 M of 65.51 M), in Spain for 87.1% of total population (40.7 M of 46.73 M), in Greece for 71.5% of total population (7.4 M of 10.34 M), and in Portugal for 83.7% of total population (8.5 M of 10.15 M). However, SM users in Italy at the beginning of 2022 were 71.6% of the total population (43.2 M of 60.32 M). While 71.6% depicts a widespread behavior in line with the other countries, one could wonder why Italy is positioned in the lower end of SM usage (almost 15% less than the upper-end countries): perhaps, the Italian population is different than other populations in some dimensions impacting SM usage. Italy is usually clustered with other Mediterranean countries such as Spain, Portugal, and Greece, but the percentage of SM users is more in line with countries such as Bulgaria, in which 64.8% of the total population use SM (4.45 of 6.87 M) or Romania, in which 69.7% of the total population does (13.30 M of 19.08 M). As an example, of the mentioned countries and according to the same source, the Italian median age is the highest: 48.0 years old, suggesting that an older population might be more resistant to social network penetration. Recently, in order to explore patterns of SM use in non-English speaker populations, other authors translated and validated this tool in Spanish and adapted it to the Brazilian context [51]. Given Italian peculiarities, we aim to do the same by translating SME-Q into Italian and adapting and validating it.

1.2. Main Aims and Scope. Considering the peculiarities of social media use in the Italian context in relation to other European countries which have been described above, a validated Italian version of the tool is required to investigate social media engagement. Therefore, our research questions concern the dimensionality of SME-Q in the Italian context and the relationship that entertains with other variables that are known to be associated with SME-Q in other countries. In order to assess the external validity of the scale, theoretically and empirically related measures which have been identified will be presented below in the Preregistered Hypothesis Development section. The study outline, data collection, and analysis plans were preregistered on http://AsPredicted.org, on July 13, 2021, and deposited on the project's website on the Open Science Framework. All data and materials are available at https://osf.io/pq4mr/.

1.2.1. Preregistered Hypothesis Development. The hypotheses were formulated taking into account the theoretical connection that should exist between the constructs, followed by the empirical evidence of other studies which have already investigated the relationship between SME-Q and the variables of interest.

Based on what has just been described about social media addiction, a positive relationship is expected between social media engagement and social media addiction [46–48].

Hypothesis 1. SME-Q is expected to entertain a positive correlation with social media addiction [46–48].

To validate the Social Media Engagement Scale in Italian, it was necessary to understand what relationships the scale entertained with other external measures investigated by scholars.

The SME-Q has been associated with trait anxiety or dispositional anxiety [46, 52–54], and in general, the studies agreed on identifying a positive relationship between the two constructs with an effect size around 0.2. This appears in line with the theory that people with greater levels of dispositional anxiety may spend more time on social media [4, 30, 55].

Hypothesis 2. It expected social media engagement to entertain a positive correlation with anxiety [46, 52–54].

Neuroticism, the opposite of emotional stability, is one of the 5 personality traits (along with extraversion, agreeableness, conscientiousness, and openness to experience) according to the Big Five model [56]. Blackwell et al. [46] describe a small positive correlation between neuroticism and SME-Q, while no significant relationships with other personality traits were observed. In addition to the use of the SME-Q, various studies and meta-analyses have investigated the relationship between neuroticism and the use of social media, demonstrating positive correlations between the two constructs. There are some differences based on the specific definition of the use of social media and the measurement tools used, but, especially when the problematic aspects of the use of social media are considered, the two constructs positively correlate [57, 58].

Hypothesis 3. It expected social media engagement to entertain a positive correlation with neuroticism personality trait [46].

The FOMO construct was firstly introduced by Przybylski et al. [16], along with the SME-Q development. The authors advanced an empirically based and theoretically meaningful framing of the phenomenon, which has been defined as "a pervasive apprehension that others might be having rewarding experiences from which one is absent" and "characterized by the desire to stay continually connected with what others are doing." A substantial number of scholars tested the relationship between FOMOs and SME-Q [16], and all confirmed a positive association between the two variables with an effect size around 0.3-0.4 [46, 48, 52–54, 59–62].

Hypothesis 4. It expected social media engagement to entertain a positive correlation with fear of missing out (FOMO) [46, 48, 52–54, 59–62].

Some evidence suggested that social media engagement could entertain a positive relationship with loneliness, although very small effect sizes were detected (under 0.2) [54, 62], in line with the theory that those who are most alone are more likely to use social media, possibly as a strategy to reduce loneliness through seeking social support [9, 26].

Hypothesis 5. It expected social media engagement to entertain a positive correlation with loneliness [54, 62).

Given their socially inherent nature, social media can be effective tools for developing and maintaining social capital [63–65]. In fact, social media engagement seems to positively associate with the levels of Internet social capital in its two subcomponents: bonding social capital ($r = .18$) and bridging social capital ($r = .21$) [66].

Hypothesis 6. It expected social media engagement to entertain a positive correlation with Internet Social Capital (ISC) [66].

All the studies recovered from the literature agree in reporting a negative relationship between social media engagement and age [16, 48, 54, 62]. Hence, these results suggest that young people are more engaged in social media (effect size around 0.2).

Hypothesis 7. It expected social media engagement to entertain a negative correlation with participants' age [16, 48, 54, 62].

Most of the studies confirmed the absence of a relationship between sex/gender and social media engagement [16, 48, 54, 62, 66].

Hypothesis 8. It expected social media engagement to entertain no relationship with participants' sex [16, 48, 54, 62, 66].

2. Methods and Procedure

All data were collected through a single survey using the Google Forms platform. The sample was collected using convenience sampling techniques such as snowball sampling by reaching participants via social media contacts. Participants were asked to fill out a Google Forms questionnaire shared through WhatsApp, Facebook, Instagram, and email. In the first part, a brief description of the study and the time it took to complete were presented, along with the contact details of the research representatives. The second part contained the informed consent and the privacy policy. Participants had to answer "I agree" or "I do not agree" to decide whether to give a consensus or not. Participants' age and gender were measured through ad hoc questions in the sociodemographic form, along with marital status and educational level. About 10 minutes were required to complete the survey. Data collection lasted from July 2021 to April 2022. A total of 520 volunteers took part in the research by filling out the entire form. Three attention check questions were included to evaluate participants' concentration in responding to the questionnaire. Those who failed more than one out of three checks were excluded from the analyses. In particular, 161 (30.96%) failed the first answer, 72 (13.85%) failed the second, and 52 (10.00%) failed the third. Following this procedure, 75 participants (14.42%) were eliminated from the sample.

2.1. Participants. Thus, the final sample consists of 445 participants who reported an adequate level of attention (maximum one error out of three). Of 445, 298 were cisgender female (66.97%), 133 were cisgender male (29.89%), 2 were transgender female (0.45%), 3 are not binary (0.67%), and 8 people preferred not to say (1.79%). Age ranged from 14 to 72 ($M = 29.91$, $\mathrm{SD} = 12.54$). Educational level ranged from "middle school diploma" to "Specialization/PhD": 35 participant reported "middle school diploma" (7.87%), 156 reported "high school diploma" (35.06%), 139 reported "Bachelor's degree" (31.24%), 87 reported "Master's degree" (19.55%), 14 reported "University master" (3.15%), and 14 reported "Specialisation/PhD" (3.15%). In terms of marital status, 166 (37.30%) were single, 193 (43.37%) were in a relationship, 82 (18.43%) were married, 3 (0.67%) were divorced, and 1 (0.22%) was widowed.

2.2. Measures. In addition to the battery of the following questionnaires, a demographic questionnaire was also presented. Participants had to indicate their age, gender, educational level, civic status, and educational level.

2.2.1. Ten Item Personality Inventory (TIPI; [67]). In order to assess personality traits, the TIPI Scale [67], in its Italian version validated by Chiorri et al. [68], was utilized. The scale assesses the five personality traits (extroversion, agreeableness, conscientiousness, neuroticism, and openness) with ten items on a 7-point Likert scale ranging from "disagree strongly" to "agree strongly." The scoring range for each dimension varies between a minimum of 2 and a maximum of 14.

2.2.2. STAI-Trait Anxiety Inventory (STAI; [69]). Trait anxiety was measured through the STAI-Y2 form of Spielberger [69], in its Italian version validated by Pedrabissi and Santinello [70]. STAI is a psychological inventory that consists of 40 self-report questions, divided into two scales that focus on how people generally feel (trait anxiety) or on how they feel in that particular moment (state anxiety). In the present study, only the trait anxiety scale was used. The trait anxiety scale consists of 20 items rated on a 4-point Likert scale (from 1 = "hardly ever" to 4 = "almost always") (e.g., "I feel nervous and restless"). Internal consistency coefficients for the scale have ranged from 0.72 to 0.96 [71]. The scoring range varies between a minimum of 20 and a maximum of 80.

2.2.3. Emotional and Social Loneliness [72]. Loneliness was measured by the emotional and social loneliness of Gierveld and Tilburg [72] in its Italian version preliminary validated by Guazzini et al. [2]. The scale presents 11 items on a 5-point Likert scale graded from disagree strongly to agree strongly. The scale assesses the two dimensions of emotional loneliness (i.e., feeling of missing an intimate relationship) and social loneliness (i.e., feeling of missing a wider social network). The scale can be used as a one-dimensional measure ($\alpha = .84$) or choose to use two subscales (one for emotional loneliness and one for social loneliness, with $\alpha = .88$ and $\alpha = .88$, respectively). The scoring range varies between a minimum of 11 and a maximum of 55 for the full scale, the theoretical score of the emotional loneliness subscale varies between 6 and 30, and the theoretical score of the social loneliness subscale varies between 5 and 25.

2.2.4. Social Media Engagement Questionnaire (SME-Q; [16]). This scale, sometimes also labeled as the Social Media Engagement Scale (SMES), is a 5-item scale that measures the extent to which people use social media during the day (e.g., "within 15 minutes of waking up"). The measure is on an 8-point Likert scale from 1 = not one-day last week to 8 = every day last week). Principal component analyses of the original scale indicated the five items loaded onto a single factor, explaining 59.27% of the observed variability, so scores were summed to create one social media engagement score for each participant ($\alpha = .82$, $M = 9.33$, $\mathrm{SD} = 7.00$) [16]. We adopt a forward and backward translation process to adapt the instrument to the Italian language following the protocol described by Beaton et al. [73]. More specifically, the scale was translated by 2 Italian psychologists into Italian, and then, the Italian items were back-translated by two native English translators (who had never seen the scale before) into English. All translators compared all forward and backward translated versions to consolidate and develop an interim Italian version of the SME-Q. The scoring range varies between a minimum of 8 and a maximum of 40.

2.2.5. Fear of Missing Out Scale (FOMOs; [16]). FOMOs [16], in its Italian version validated by Casale and Fioravanti [74] was utilized to measure fear of missing out (FOMO), which consists of the pervasive apprehension that others might be having rewarding experiences from which one is absent and the desire to stay continually connected with what others are doing (e.g., "I fear others have more rewarding experiences than me"). The scale is composed of 10 items on a five-point Likert-type scale (1 = "Not at all true of me," 2 = "Slightly true of me," 3 = "Moderately true of me," 4 = "Very true of me," and 5 = "Extremely true of me"). The original scale showed a unidimensional model with a good consistency ($\alpha = .87$) [16]. The Italian validation showed a two-factor solution explaining 50.66% of the total variance. The CFA confirmed a two-factor solution with adequate fits for the Italian FOMOs (Cronbach's coefficient alphas were $\alpha = 0.79$ for factor 1 (fear) and $\alpha = 0.73$ for factor 2 (control) [74]. The scoring range for the total scale is between a minimum of 10 and a maximum of 50. The scoring range is 4-20 for the fear subscale and 6-30 for the control subscale.

2.2.6. Internet Social Capital Scale (ISCs; [65]). Internet Social Capital was measured with the ISCs of Williams [65]. We adopted a forward and backward translation process to adapt the instrument to the Italian language according to Beaton et al. [73]. The instrument assesses the dimensions of bridging social capital, which brings people together through social networks that are not similar to each other (e.g., school) and bonding social capital, which reinforces close ties of people with similarities in key aspects (e.g., close friends). The original scale allows for measuring both online and offline social support levels. This study only adopts the online scale (20 items). All questions are statements in the form of a 5-point "strongly disagree" to "strongly agree" Likert scale. Sample items are "There is someone online/offline I can turn to for advice about making very important decisions" for the bonding dimension and "Interacting with people online/offline reminds me that everyone in the world is connected" for the bridging dimension. The Cronbach's alpha for the complete online bridging and bonding scale was .900 ($\alpha = .896$ for the online bonding factor; $\alpha = .841$ for the online bridging factor). The scoring range for each dimension varies between a minimum of 10 and a maximum of 50.

2.2.7. Bergen Social Media Addiction Scale [44]. Social media addiction was measured by the BSMAS of Andreassen et al. [44] in its Italian version provided by Monacis et al. [75]. The BSMAS contains six items reflecting core addiction elements (i.e., salience, mood modification, tolerance, withdrawal, conflict, and relapse; [45]). Each item refers to experiences from the previous 12 months, and the answer mode is on a 5-point Likert scale that ranges from 1 (very rarely) to 5 (very often). A sample item is "How often during the last year have you felt an urge to use social media?" The internal consistency of the BSMAS is high both in the original and Italian versions ($\alpha = 0.88$). The scoring range varies between a minimum of 6 and a maximum of 30.

2.3. Statistical Analysis. Before recruiting participants, we tried to identify an adequate sample size for the study. For confirmatory factor analysis (CFA), we relied on the 10 : 1 participants: item ratio rule [76], and thus, 50 participants would have been enough. Nonetheless, several power analyses were performed because the use of Pearson's correlation and two Welch's t-tests (for sex-related differences) was planned. In order to accomplish this procedure, G*Power software was used [77, 78]. The target sample size was selected by relying on the power analysis requiring the largest sample size. For testing sex-related differences, a sample of 430 individuals was required in order to reach a statistical power of 0.80, supposing a small-medium effect size ($d = .30$) and an expected gender ratio of 1 : 2.5. For Pearson's correlation, a sample of 425 was required to achieve the same statistical power (i.e., .80), while assuming a smaller effect size ($r = .13$). The final and recommended sample size has thus been fixed at 430. Therefore, our sample size of 445 is adequate.

For CFA, we used maximum likelihood estimation (MLE) to estimate the parameters of the model. We used several goodness-of-fit indices to evaluate the model fitness: the $\chi2$/df (ratio between chi-square and degrees of freedom; [79]), the TLI (Tucker-Lewis index; [80]), the CFI (comparative fit index; [81]), the SRMR (standardized root mean square residual; [82]), and the RMSEA (root mean square error of approximation; [83]). Acceptable values for both CFI and TLI are higher than .90, while values higher than .95 are considered optimal. Acceptable fit for the RMSEA requires values smaller than .08, while the optimal fit is expressed by values close to .06. For SRMR, it recommended a cutoff value below .08 [84, 85]. Eventually, SME-Q reliability was assessed through Cronbach's alpha, McDonald's omega, and Pearson's correlation. Common-method bias was also assessed with Harman's single-factor test without detecting any problem for proceeding with the analyses [86].

3. Results

3.1. Descriptive Statistics. As a first step, we produced the descriptive statistics for all SME-Q items (Table 1), and we compared our values with those coming from the English version of Przybylski et al. [16] through a Student's t-test.

As shown in Table 1, for all the items, differences ranging from medium to large were detected following the well-established Cohen's cutoffs (0.2 for small effects, 0.5 for medium effects, 0.8 for large effects; [87]). The Italian version items always showed higher SME-Q values with respect to the original scale probably due to the exponential growth of smartphones and social media in the 9 years from the publication of the original scale [16, 88].

3.2. Confirmatory Factor Analysis and SME-Q Reliability. CFA was performed on the SME-Q items to investigate the factorial structure of the construct. First, the five items (i.e., exogenous variables) were used as indicators of a single latent variable, as envisaged by the work of Przybylski et al. [16]. As shown in Table 2, the original model (i.e., model 0) led to unsatisfactory fit indices. Based on modification index (M.I.) analysis, we let item 1 and item 2 errors covary (model 1), since covariated errors may arise from items that are similarly worded, like in our case [89]. Despite this first modification, the model was unable to explain data in a satisfactory way. Therefore, we let errors of items 1 and 5 covary as suggested by M.I. analysis (model 2). Nonetheless,

Table 1: Descriptive statistics of the SME-Q Italian version.

N°	Item	Min	Max	Mean	SD	t	d
1	Entro 15 minuti dopo che ti sei svegliato	1	8	5.50	2.76	-36.96^{***}	-1.94
2	Durante la colazione	1	8	4.10	2.85	-24.54^{***}	-1.29
3	Durante il pranzo	1	8	3.17	2.58	-11.03^{***}	-0.58
4	Durante la cena	1	8	2.69	2.38	-10.51^{***}	-0.55
5	Negli ultimi 15 minuti prima di andare a dormire	1	8	6.36	2.41	-37.12^{***}	-1.95

Table 2: Results of confirmatory factor analysis. The table reported the fit indexes for each tested model. See text for details.

Models	χ^2/df	TLI	CFI	RMSEA	SRMR
Model 0	42.58	0.47	0.74	0.306	0.145
Model 1	27.35	0.67	0.87	0.244	0.119
Model 2	9.63	0.89	0.97	0.139	0.056
Model 3	1.544	0.99	0.99	0.035	0.008
Model 4	28.20	0.66	0.86	0.25	0.107
Model 5	3.062	0.98	0.99	0.068	0.009

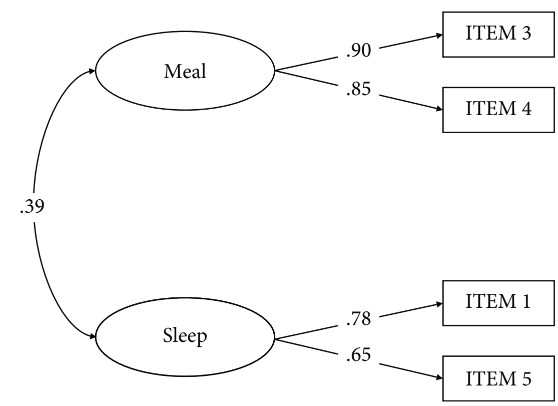

Figure 1: Results of confirmatory factor analysis of the SME-Q two-factor model (model 5).

CFI and SRMR were the only indices surpassing the thresholds for an acceptable fit. Adding a final covariance link between errors of items 2 and 5 (model 3), the model met all the required values for model fit. However, the need to add so many covariance links paired with item 1 (0.30) and 5 (0.25) unsatisfactory factor loadings (i.e., they were lower than the conventionally acceptable threshold of >.50) suggested considering other possible structures for the Italian version of the SME-Q. After analyzing the item wording, the authors considered a bifactorial structure based on the two main domains possibly envisaging social media use: around sleep time (items 1 and 5) and during meals (items 2, 3, and 4). Model 4 did not achieve an acceptable fit; however, compared to model 0, this model showed better goodness-of-fit indices. By looking at M.I., which suggested a covariance link between item 2 and sleep factor (91.04), as well as its factor loading (0.49), we decided to eliminate the item for model 5. After the removal of item 2, the CFA showed an optimal fit for the SME-Q two-factor model. Moreover, all factor loadings resulted statistically significant and higher than >.50 (Figure 1).

For assessing Italian SME-Q reliability, we relied also on Pearson's correlation since scholars from different fields claimed that Cronbach's alpha coefficient and McDonald's omega could be inappropriate and meaningless for two-item scales like in our case [90–93]. Item 1 and item 5 were strongly correlated ($r = 0.51$; $p.<0.001$; $\alpha = 0.67$; $\omega = 0.67$) as well as item 3 and item 4 ($r = 0.77$; $p.<0.001$; $\alpha = 0.87$; $\omega = 0.87$). In general terms, the meal dimension appeared more reliable than the sleep one.

3.3. Validity. To externally validate the Social Media Engagement Questionnaire (SME-Q) in the Italian context, we followed the preregistered hypotheses. Before that, we produced descriptive statistics and report them in a sex-sensitive way (i.e., disaggregating data by sex; Table 3).

To understand whether sex should be accounted for as a possible confounding variable for testing hypotheses from 1 to 7, we first compared males' and females' scores on the two dimensions of the SME-Q (H8) through Welch's t-tests since sample sizes were unequal between groups. Neither the meal dimension ($t_{(256.26)} = -0.23$; $p. = 0.82$) nor the sleep one ($t_{(247.45)} = -1.58$; $p. = 0.12$) appeared to be different across males and females. Given that, we did not include sex as a possible covariate for assessing SME-Q relationships with metric external validation measures (Table 4).

As reported in Table 4, both FOMO dimensions and total score entertained a positive relationship with SME-Q (Hypothesis 1). More specifically, and following Gignac and Szodorai [94] rules of interpretation, SME-Q meal appeared to be correlated in a typical fashion with FOMO-related variables, whereas SME-Q sleep is relatively largely correlated with FOMO. Anxiety and neuroticism were found positively correlated with both SME-Q meal and SME-Q sleep (Hypothesis 2 and Hypothesis 3). Even in these cases, the correlation of anxiety and neuroticism with SME-Q appeared stronger for the sleep dimension. Instead, SME-Q and loneliness appeared mostly independent (Hypothesis 4). The only but negligible exception is represented by the small positive relationship between emotional loneliness and SME-Q meal. Internet Social Capital was positively related to both SME-Q dimensions (Hypothesis 5). In particular, the magnitude between the bonding dimension of ISC and both SME-Q meal and SME-Q sleep is almost the same (typical), whereas we observed a wider difference in magnitude considering ISC—bridging with SME-Q sleep being correlated in a relatively large way and SME-Q meal

Table 3: Descriptive statistics of the collected data also disaggregated by sex.

	Total sample (N = 445)	Males (N = 133)	Females (N = 298)
Variables	M (SD)	M (SD)	M (SD)
SME-Q meal	5.85 (4.66)	5.69 (4.58)	5.80 (4.63)
SMEE-Q sleep	11.85 (4.48)	11.35 (4.54)	12.10 (4.42)
FOMO—total	22.65 (7.19)	21.55 (6.17)	23.11 (7.46)
FOMO—fear	8.41 (3.70)	7.90 (3.17)	8.63 (3.86)
FOMO—control	14.24 (4.20)	13.65 (3.61)	14.48 (4.36)
Anxiety	46.36 (11.19)	44.56 (10.39)	16.99 (11.41)
Neuroticism	8.12 (2.77)	7.29 (2.75)	8.51 (2.69)
Loneliness—social	12.00 (4.23)	11.90 (4.21)	11.96 (4.15)
Loneliness—emotional	15.36 (5.26)	15.22 (4.94)	15.33 (5.39)
ISC—bonding	18.23 (6.44)	19.95 (6.54)	17.41 (6.18)
ISC—bridging	30.09 (8.10)	31.29 (7.80)	29.52 (8.02)
BSMAS	13.75 (5.08)	12.51 (4.75)	14.28 (5.08)

Note: M = mean; SD = standard deviation; SME-Q = Social Media Engagement Questionnaire; FOMO = fear of missing out; ISC = Internet Social Capital; BSMAS = Bergen Social Media Addiction Scale.

Table 4: Correlation matrix of SME-Q relationship with metric external validation measures.

Variables	SME-Q meal	SME-Q sleep
Age	-0.14^{**}	-0.43^{***}
FOMO—total	0.26^{***}	0.32^{***}
FOMO—fear	0.23^{***}	0.27^{***}
FOMO—control	0.24^{***}	0.31^{***}
Anxiety	0.16^{***}	0.21^{***}
Neuroticism	0.15^{***}	0.24^{***}
Loneliness—social	-0.02^{ns}	-0.06^{ns}
Loneliness—emotional	0.09^{*}	0.06^{ns}
ISC—bonding	0.18^{***}	0.23^{***}
ISC—bridging	0.14^{**}	0.29^{***}
BSMAS	0.30^{***}	0.33^{***}

Note: $^{*}p.<0.05$; $^{**}p.<0.01$; $^{***}p.<0.001$; ^{ns} = not statistically significant; FOMO = fear of missing out; ISC = Internet Social Capital; BSMAS = Bergen Social Media Addiction Scale.

in a more moderate way. Social media addiction appeared largely and positively correlated with both SME-Q components (Hypothesis 6). Finally, age was negatively associated with social media engagement (Hypothesis 7) while no relationship was found between social media engagement and participants' sex (Hypothesis 8).

4. Discussion

Social networks continue to evolve and become more intertwined with our lives because of their ability to satisfy multiple human needs. Data on social media use around the world consistently report an increase in frequency and adoption, especially during the COVID-19 pandemic, suggesting that social isolation facilitates social media use [8, 9]. In addition to increased use, there is a need to understand the effects of social media on individuals. Several studies have attempted to understand the mental health implications [30, 55], including negative effects on sleep patterns and quality [32, 41–43], and personal and interpersonal implications related to phubbing behavior [35–37]. Scholars have examined technoference, or the intrusion of technology into daily life [28, 34], but also the positive features of social media that can promote well-being [25–27].

In this paper, we validated the Italian version of the SME-Q, a tool developed to avoid considering engagement with SNS as problematic or focusing on negative consequences. We carried out both an internal and an external validation in order to obtain a tool for the study of such phenomena within the specificities of the Italian context. First, the factorial structure of the Italian version of the SME-Q was analyzed. While the original factorial structure described a single latent variable, the Italian data were better represented by two factors, i.e., a factor related to the use of SN around sleep time and a factor related to the use during meals. The reliability of the bifactorial scale indicated that the meal dimension was more reliable than the sleep dimension. Second, to test external validation, measures for all the hypothesized related variables were used, and the correlation with each of the two SME-Q factors was calculated. Both factors of the SME-Q have been found to correlate with social media addiction, anxiety, neuroticism, and fear of missing out, confirming Hypothesis 1, Hypothesis 2, Hypothesis 3, and Hypothesis 4. In these cases, the correlation was stronger for the sleep factor. Contrary to expectations, loneliness seemed to be almost unrelated to the SME-Q factors, rejecting Hypothesis 5. It should be noted that studies that specifically take SME-Q and loneliness into consideration are few and identify small relationships that do not seem very robust. Furthermore, our study took place in the COVID era, which may have implied some specific differences with these studies and specific effects, such as an increase in the general sense of loneliness in the population and an increase in social media engagement, as well as a change in the relationship between technology and coping strategies [2].

Both SME-Q factors were positively correlated with Internet Social Capital variables to a similar extent, except for ISC—bridging, which was more strongly correlated with SME-Q sleep, but more moderately correlated with SME-Q meal, confirming Hypothesis 6. There was a negative association between age and SME-Q factors, while sex appeared to be unrelated, supporting both Hypothesis 7 and Hypothesis 8.

Clearly, our results regarding external validation are correlational, and no causation can be inferred. Moreover, our results are based on a biased sample due to a nonrandom sampling technique and self-selection bias. Therefore, the generalizability of our results to the whole Italian population is very limited, and future replication of the study is encouraged. A possible measurement bias is also acknowledged due to the fact that the authors had to translate the Internet Social Capital Scale [65] since an already existent and validated Italian version was not available. Future research should deal with these limitations, as well as replicate this study involving specific social media users (e.g., TikTok, Instagram, and YouTube) to assess the robustness of these results.

Considering the psychological aspects and the implications related to the use of social media during key moments of the day (i.e., during meals or around sleep time), the bifactorial nature of the scale can be useful for the development and implementation of educational paths about the conscious use of new technologies. Indeed, promoting an informed and responsible use of these technological tools can ultimately foster personal and social well-being.

Moreover, the use of this quick scale might also would allow the identification of populations potentially at risk of engaging with social media at times of the day when the use of social media is not advisable.

Finally, by identifying social media usage patterns, this questionnaire also paves the way for technology management tools [95, 96], such as coaching apps [97] or options for SNS applications designed for monitoring and limiting the use of devices according to the user's needs [98].

5. Conclusion

In conclusion, the Italian translation and adaptation, despite having a different factorial structure from the original SME-Q, shows adequate psychometric characteristics to be used as a measurement tool. This measurement tool allows for a quick assessment of the level of social media engagement experienced by an individual and thus can be used as a brief assessment tool to provide a snapshot of an individual's social media engagement patterns.

Data Availability

The data used to support the findings of this study have been deposited in the Open Science Framework repository (https://osf.io/pq4mr/).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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