

Research Article

Development and Validation of the Social Media Capital Scale (SMC): A Brand New Measure for Online Social Capital

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We conducted a series of studies in order to develop a tool to assess social media capital, that is, more specifically, individual confidence in the use of social media sites and in their application to maintain and increase social capital. In our first study, we created the social media capital (SMC) scale by adapting parts of two already existing instruments and administered it to 6935 people to test its psychometric properties and dimensionality. After having validated the SMC in its final 7-item form, we proceeded to assess its external validity in two subsequent studies, by testing it against measures for Internet self-efficacy (study 2; $n = 3100$) and motives to use the Internet and social media addiction (study 3; $n = 244$). Overall, the SMC displayed satisfactory psychometric properties and appears to be a sound measure of social media capital.

1. Introduction

In today's world, new social media are increasingly present in the everyday life of each individual. By social media, Kaplan and Haenlein [1] mean “a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0 and that allow the creation and exchange of user-generated content” [1].

The Global Social Media Stats report reveals that there are currently 4.33 billion social media users worldwide, which is more than 55% of the total global population. The average user seems to spend almost 2 and a half hours a day using these platforms, or about 15% of their waking life. This pervasiveness of use may also be partly due to the increase in polychronic media, whereby people use multiple types of media simultaneously, for example, by messaging with friends online via smartphone while, at the same time, watching television or working at the PC [2, 3].

The ever increasing diffusion of these new technologies changed, in particular, the way people relate, providing greater opportunities for connection, communication, and

interaction between individuals [4]. The emergence of social media as preferential means of communicating with each other can guarantee a better maintenance of existing social ties, a greater development of social capital, or the creation of a new form of social capital associated with the use of social media themselves [3, 5].

Given the increasing popularity of social media and the related research in this topic, we decided to develop a scale to assess people's confidence in the use of these tools for fostering their social capital (both bridging and bonding oriented). Several studies have shown that online social capital is associated to higher levels of well-being and several positive outcomes (i.e., [6–10]), and the recent pandemic has been an example of how social media can be effectively used by many to obviate the lack of in person interactions, given however a certain degree of efficacy in their use [11–15]. Therefore, a tool to measure social media capital is fundamental and timely and could have several use, for example, to evaluate the efficacy of interventions aimed at fostering the development of interpersonal relationships through the Internet, when face-to-face interactions are limited.

2. The Relationship between Social Media and Social Capital

Social capital is defined as “the aggregate of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance or recognition” ([16], p. 248). The main source of this set of resources is, therefore, interpersonal relationships, which according to Putnam [17] are divided into two main types: *bonding* and *bridging*. By bonding, we mean all those bonds between people with similar characteristics (for example, people who are part of the same ethnic group or religion). With bridging, on the contrary, we describe all those relationships between individuals with different characteristics [17].

Social media capital can be defined as the social capital an individual develops and maintains through the use of social media sites and applications.

In recent decades, several studies have been carried out to verify whether the use of these digital media actually fed the social capital of users, who for the most part confirmed this hypothesis [18–20]. In particular, some scholars show how social media influenced bridging social capital in a more evident way [19, 21, 22]. In line with these findings, some studies have shown that social media does not seem to work for maintaining bonding relationships [23, 24]; rather, they may allow more efficiently to create new ties than to strengthen existing ties offline [25, 26].

The study of Bohn and colleagues [18] showed that sharing content via social media and the frequency of use of these is important for developing social capital and can have a positive influence on its development, but excessive use can be harmful to the same [18, 26]. Moreover, factors such as self-efficacy, social presence, and self-affirmation act as mediators for online social capital; i.e., the higher they are, the greater the social media capital [26, 27].

Several studies have highlighted the positive impact that the use of social media to develop and/or maintain social capital can have on people’s lives, as it is associated to higher psychological well-being [6] and life satisfaction [10] as well as to lower levels of loneliness [8], social isolation [28], and depression [29]. It has also been shown to be beneficial to disadvantaged populations, for instance, by promoting positive health outcomes in terms of stress, depression, and coping in cancer patients [30] and a higher life satisfaction in trailing parents [31].

We are surrounded by tools with greater entertainment potential than those of a decade ago. We can mention, for example, a social network developed only in 2016, which spreads a series of short videos on the platform, in rapid succession: *TikTok*. It can be thought that behind the use of this tool there is not really the need to socialize; in reality, thanks to various researches, it has been discovered that the use of this platform affects the social life of users in a positive way, if frequently used [32, 33]. Among the main reasons that push people to use it, in addition to those of “motivation to acquire information” and “motivation to present oneself,” it can be noted that interpersonal communication is also predominant. Additionally, thanks to a study by Yang [33],

the above reasons emerge as correlated links with bridging and social capital [33].

As for the more traditional platforms, such as the now dated *Facebook*, a social network born mainly as a push to increase one’s social capital or to keep it active thanks to the sharing of posts, photos, and a private chat with one’s circle of “friends,” several studies have been developed on the relationship between Facebook and social capital development [20, 34, 35]. An interesting study by Kahai and Lei [36] compares the use of Facebook with that of even more traditional media: their study showed that Facebook interacts with the use of traditional media for building relationships. Specifically, the use of Facebook promotes bridging social capital to a greater extent with respect to traditional media but mainly when the latter are infrequently used. A further study result shows that users go to greatly improve their social capital, especially when they interact with older friends [36]. Consistent with the studies concerning previous social media, while taking into account to the widespread use *Instagram*, we follow the same thought process: there are different ways to establish a social connection with other users through Instagram, such as following advice from an “influencer” or by putting a reaction to a photo or video of the other users followed [37]. From several studies, it emerges that this is the best social media that allows an increase in social capital compared to the others: the active use of Instagram seems to have a strong impact with the development, in particular, of social support [32].

3. The Relationship between Social Media Usage and Internet Self-Efficacy

The adoption of social media therefore appeared to depend also on users’ confidence in their ability to successfully understand, navigate, and evaluate content online [38]. In particular, from a Wang et al., [39] study, it emerged that Internet self-efficacy was a significant social function predictor of social media use [39]. According to “self-efficacy theory,” users’ Internet and social media self-efficacy should grow in parallel with their expectations of obtaining specific positive outcomes from those media, thus resulting in further usage. On the other hand, lacking such expectations, users with lower self-efficacy should be less likely to engage in Internet and social media-related activities [3, 40].

Self-efficacy is described as the belief of being able to perform a certain task [41]. In the context of the Internet, the most self-effective people feel more capable of acquiring skills in using Internet services and in maintaining an active online connection [42, 43]. Similarly, it is understandable that a user who feels effective in the general use of the Internet and technology perceives a greater ease of use even of social media and uses them more frequently. The basis of this hypothesis is supported by various studies that confirm this association [44–47].

Moreover, a positive relationship between Internet self-efficacy and online social capital, as well as with regard to online social interactions, is reported by literature [48]. This may indicate that the perception of being able to surf the Internet has a certain influence on the willingness to

communicate with each other thanks to the help of technology, as social media allows us to do. Furthermore, the Internet is widely used as a knowledge sharing tool, and this also seems to depend heavily on the Internet self-efficacy of users [49]. Sharabati [50] argues that self-efficacy in sharing knowledge online is crucial for user behavior in social media contexts. This indicated that there was also a close relationship between this type of Internet self-efficacy and content sharing via social media.

4. The Role of Age, Sex, and Internet Motivations

Another interesting fact that emerges from the literature is that age negatively predicted the use of the Internet and social capital [9]. These findings may be linked to the fact that older people tend to be less accustomed to using the Internet and social media with respect to younger users which in turn are assumed as perceiving greater Internet self-efficacy and confidence in their ability to use social media sites. It is also pointed out that the number of social bonds tends to decrease with age due to changes in lifestyle [9, 51–53]. This probably makes younger people more likely to have the skills needed to more easily use the Internet and to further develop their online social capital, widening the gap with older people who cannot rely on the same array of skills.

For all these reasons, we decided to test the external validity of our scale by verifying the correlation with the various dimensions of the Internet self-efficacy scale (ISS; [54]).

Over the years, the success and spreading of social media usage among several kinds of users has led to an exponential thinning of gender differences in terms of confidence or self-efficacy in the use of social media. In fact, although there seems to remain gender differences regarding other aspects such as addiction [55] and use motivations [56], literature does not show substantial results regarding gender differences in social media confidence.

As we already described above, Internet self-efficacy is a disposition that reflects one's confidence using the Internet. LaRose et al. [57] found that Internet self-efficacy positively predicted deficient Internet self-regulation. They speculated that deficiency of Internet self-regulation might be closely associated with Internet addiction, although they did not examine the relationship specifically. Moreover, they contended that using the media for certain reasons, such as to pass the time, alleviate boredom, seek parasocial interaction, or validate social identity, may result in a deficient self-regulation of media use.

On the other hand, according to some authors, spending too much time on the Internet might be more related to individual motivations to get online than to Internet self-efficacy. For instance, Shapka [58] highlights that for adolescents, who spend the most time online than any other demographic, the Internet and social media can be an effective and efficient means to socialize and to satisfy the impellence of their social needs. Therefore, the substantial and seemingly excessive time they spend online should not be considered the result of a lack of self-regulation, rather it should be ascribed to the absence of an incentive to self-regulate. In other words, they might be actively

and purposely regulating towards the goal of increasing and maintaining their social capital.

In addition, a study of Sun [59] indicates that self-efficacy positively predicted interpersonal utility motivation, pass-time motivation, and entertainment motivation.

Reading these results, we could expect that social media confidence could be associated with Internet use motivation.

5. Social Media and Digital Addictions

Confidence in using the Internet and social media sites may also be considered a common feature in various digital addictions, such as those to the Internet or social media. The reason is that an addiction to any of these means implies by definition a conspicuous amount of time spent using such a means, which one may expect to result in the individual being significantly accustomed to, and thus confident with, using it. Given the low employment of the Internet and social media confidence measures, to our knowledge, there does not seem to be any study assessing any direct association between digital addictions and such constructs. Nonetheless, several sources have found a higher usage of the Internet to be associated with the Internet, social media, and smartphone addictions [60–63]. Others have also found it to be correlated to a higher Internet self-efficacy [64, 65], which in turn is associated with an increased social media self-efficacy [44]. Likewise, we could expect a more frequent Internet and social media usage from those who already feel confident with those means, as Bright and colleagues [3] have pointed out.

6. Aim of the Study

Our goal was to develop an instrument to assess social media capital, by which we mean people's confidence in their ability to use social media (SM) in order to stay connected with others. As we have seen, the relation between Internet and SM use, on one hand, and social connectedness, on the other, is significant but complex and strongly influenced by one's skills with online platforms. Numerous studies have consistently shown how the Internet and SM use can have several positive effects, as it is correlated to

- (i) increased social capital [5, 26, 66], in particular by strengthening one's network of weak ties [53, 67]
- (ii) higher levels of perceived social support [68–70] and sense of community [5, 71, 72]
- (iii) a lower perceived loneliness [5, 73, 74] and a decreased social isolation [68, 75]

However, this seems to only be the case for those who are proficient in making use of the Internet and who already have a significant offline social network to count on. Otherwise, most of the aforementioned correlations are either not present or in the opposite direction [5, 76–78]. As an example, several studies found that age negatively predicts social capital and Internet use. Such results could be explained by considering at least two points: first, older people tend to be

less accustomed to use the Internet and SM compared to younger “digital natives” and therefore less skilled; second, research shows that the number of social ties tends to diminish with age due to life course circumstances [9, 51–53].

Neves et al. [9] have pointed out how this could be a prime example of Merton’s [79] so called “Matthews Effect,” according to which “the rich get richer at a rate that makes the poor become relatively poorer” (p.62). In other words, whereas advantage begets further advantage, disadvantage begets further disadvantage; therefore, younger people are more likely to have the necessary skills to take advantage of the Internet and increase their already developed social network capital, thus expanding the gap between them and older people who are not able to do the same. Not surprisingly, the negative effect of age on Internet and SM capabilities of nurturing social capital seems to disappear if quantity of usage is controlled for: among older adults, frequent Internet users tend to report having more social ties than less frequent users [9].

For these reasons, for the purpose of measuring social media capital, it seems necessary to take into consideration one’s confidence with SM as well as one’s ability in using the Internet as a means for social connection. To our knowledge, no other existing instrument factors in both constructs specifically, though, and those which assess one or the other present several issues.

A few measures of confidence in utilizing the Internet or SM also explore respondents’ perceived usefulness of such platforms as means to connect with other people, but they only do so incidentally, through a minor part of the items they are composed of i.e., [3, 54, 80]. Moreover, given the rapidity with which the online world has been changing over the years, many measures of Internet-related constructs could not help but quickly become obsolete along with the realities they refer to. For example, the now 20-year-old “Internet self-efficacy scale” by Torkzadeh and Van Dyke [81] has been used in numerous studies, but it has long outlived its purpose, as the several references it makes to being able to encrypt/decrypt email messages or to use a fax machine may be quite meaningless to most people. Newer measures can have the same problem, such as in the case of Kim’s and Glassman’s “Internet self-efficacy scale” (2013). It can be hard to comprehend the meaning of its “differentiation self-efficacy” subscale, given how its items concern the use of hyperlinks in order to improve one’s own or other people’s well-being or to find information that is important to the individual or to others. A whole other subscale is dedicated to the use of blogging for several purposes: although blogs are still common nowadays, the importance they are attributed in this instance is unrealistic for today’s standards.

For all these reasons, we decided to develop a measure for social media capital that was specific to the construct, up-to-date, and brief. It also had to be composed of two subsets of items, one aiming to assess the individual confidence in the use of SM and the other concerning Internet-mediated social connectedness. We expected the two constructs to be both distinct and strongly correlated one to the other, as they should be two aspects of one same construct they conjointly describe.

Our scale has been assembled by adapting and joining items from two already existing instruments. The four items that constitute the “social media confidence” subscale have been taken from the “social media self-confidence” scale [3]: to be specific, we adapted its whole “social media confidence” subscale and one item (“I find social media websites easy to use”) from the “social media self-efficacy” subscale. The other half of our social media capital scale has been derived from Sun and colleagues’ “Internet social connection” scale [82], which in turn were adapted from the 10th WWW user survey by the Graphic, Visualization, and Usability Center of Georgia Institute of Technology [83].

Once all the necessary items had been gathered, they underwent a process of translation and back translation in order to develop the Italian version of the instrument we then proceeded to administer in our studies.

7. Study 1

7.1. Methods

7.1.1. Participants. The SMC scale was administered alone in its first form (8 items) to a total of 6935 participants. The sample size was considered adequate for conducting both exploratory and confirmatory factor analyses. In our case (i.e., 2 expected factors and 8 items), based on de Winter and colleagues’ work [84], a sample size slightly lower than 370 would be enough for conducting exploratory factor analysis even assuming quite-low factor loadings ($\lambda = 0.4$). As for the sample size for confirmatory factor analysis, according to the literature, there should be at least 10 participants for each scale item [85], and because the total number of items is 8, the final sample size was deemed to be acceptable for study one. The sample for the first study was predominantly female (75.4%) with an average age of 24.15 years (standard deviation = 9.93). The recruitment was carried out by advertising the study through free open calls to action on social media platforms and online word of mouth, ensuring the anonymity of any respondent in line with Italian law’s requirements of privacy and informed consent (Law Decree DL-101/2018) and EU regulation (2016/679).

7.1.2. Data Analysis. Exploratory and confirmatory factor analyses were carried out to define the SMC dimensionality. SMC gender invariance was also tested through multigroup confirmatory factor analysis. Finally, item performance was analyzed based on item response theory, internal consistency, and item-total correlations.

8. Results

8.1. Descriptive Statistics. As a first step, we produced the descriptive statistics for all the items involved in our data collection (Table 1).

8.2. Exploratory Factor Analysis (EFA). Before investigating the SMC factor structure (i.e., EFA and CFA), the whole sample was randomly split into two samples of different sizes. Approximately 1/3 of the original sample (i.e., $N_{(EFA)} = 2326$) was employed for EFA. We relied on the principal axis

TABLE 1: Descriptive statistics of the item pool used to build the social media capital scale.

No.	Item	Min	Max	Mean	s.d.
1	ENG: I'm used to using social media. IT: Ho pratica con l'uso dei social media.	1	5	4.02	1.01
2	ENG: I feel confident in using social media. IT: Mi sento capace di usare i social media.	1	5	3.94	1.01
3	ENG: I feel comfortable using social media. IT: Mi sento a mio agio usando i social media.	1	5	3.68	1.06
4	ENG: I find social media easy to use. IT: Trovo il social media facile da usare.	1	5	4.06	0.95
5	ENG: Since getting on social media, I have become more connected to people like me. IT: Da quando sono sui social media, sono più connesso a persone simili a me.	1	5	2.94	1.18
6	ENG: Since getting on social media, I have become more connected to people who share my hobbies/ recreational activities through social media. IT: Da quando sono sui social media, sono più connesso a persone che hanno gli stessi hobby.	1	5	3.03	1.18
7	ENG: I have become more connected to people in my family through social media. IT: Sono divenuto più connesso ai membri della mia famiglia, per via dei social media.	1	5	2.08	1.17
8	ENG: I have become more connected to people in similar life situations through social media. IT: Sono diventato più connesso a persone con condizioni di vita simili alla mia, per via dei social media.	1	5	2.61	1.23

Note: $N = 6935$; s.d. = standard deviation; ENG = English version of the item not yet validated; IT = Italian version of the items that are actually validated in the paper.

factoring extraction method with Promax (oblique) rotation on the eight items of the SMC. The number of components to be extracted was defined through the scree plot examination [86] together with the Kaiser criterion (i.e., all factors with eigenvalues greater than one) [87]. The items were retained if they had factor loadings above 0.50 and parallel loadings below 0.20 [88]. Since item 7 did not match the retention criteria (i.e., factor loading = 0.41), it was excluded from subsequent analyses.

The analysis suggested a two-factor structure explaining 68.44% of the total variance of the construct (Table 2). Since the Kaiser criterion technique is sometimes not the best choice to go with for determining the number of factors to be retained [89–91], parallel analysis [92] was also carried out. The analysis compared the observed eigenvalues extracted from the correlation matrix with those obtained from uncorrelated normal variables generated through a Monte Carlo simulation process [92]. By referring to the rule that a factor should be retained if the associated eigenvalue was higher than the mean of those obtained from the random uncorrelated data, the two-factor structure appeared to be confirmed.

8.3. Confirmatory Factor Analysis (CFA). CFA was performed on the second sample (i.e., $N_{(CFA)} = 4609$) to confirm the factor structure found previously. The seven items (i.e., exogenous variables) were used as indicators of the two latent variables as represented in Figure 1. Maximum likelihood estimation (MLE) was used for estimating the model's parameters.

To evaluate the model fit, several goodness-of-fit indices were used: the chi-square to the degree of freedom ratio (χ^2/df ; [93]), the Tucker-Lewis index (TLI; [94]), the comparative fit index (CFI; [95]), the standardized root mean square residual (SRMR; [96]), and the root mean square error of approxi-

mation (RMSEA; [97]). For both CFI and TLI, values higher than 0.90 are acceptable whereas values above 0.95 were considered optimal. As for the RMSEA, values smaller than 0.08 express an acceptable fit, whereas an optimal fit is achieved with values close to 0.06. Finally, a cutoff value below 0.08 for SRMR is recommended [98, 99].

The CFA showed an optimal fit for the SMC two-factor model ($\chi^2/df = 18.19$; $p < 0.001$; TLI = 0.98; CFI = 0.99; RMSEA = 0.061; SRMR = 0.023). Moreover, all factor loadings resulted statistically significant and higher than the conventional acceptable threshold of >0.50 (Figure 1).

8.4. Gender Invariance. Subsequently, we proceeded with the multigroup confirmatory factor analysis to test SMC invariance across gender. In our case, three types of invariance have been tested by relying on chi-square differences across models: configural (i.e., the structural CFA model is assumed as equivalent for both women and men), metric (i.e., factor loadings are assumed the same across gender), and scalar (the intercepts are assumed equal between women and men). Nonetheless, since the chi-square is sensitive to sample size, we considered also changes in other fit indices (i.e., RMSEA and CFI) as a way to evaluate misfit in our invariance analysis [100, 101]. For the sake of clarity, we specify that changes in model fit indexes should be less than 0.002 for the CFI [102] and 0.010 in the RMSEA [100].

For the SMC, the difference between the configural and metric models was not statistically significant ($\Delta\chi^2$ configural-metric = 8.80; $p = 0.12$; $\Delta CFI < 0.001$; $\Delta RMSEA = 0.003$), while metric and scalar models resulted statistically different ($\Delta\chi^2$ metric-scalar = 53.56; $p < 0.001$; $\Delta CFI < 0.003$; $\Delta RMSEA = 0.001$). Thus, both structural model and factor loadings appeared equivalent across the groups.

TABLE 2: EFA results: SMC factor structure and factor loadings.

Item number	F1 loading	F2 loading
1	0.84	
2	0.87	
3	0.79	
4	0.73	
5		0.84
6		0.83
8		0.71
Eigenvalues	3.55	1.25
Explained total variance	50.65%	17.80%
Cumulative total variance	68.44%	

Theoretically, a construct should be scalar invariant; nonetheless, reaching metric invariance has been considered enough by several authors for proceeding with inferential analyses and thus testing validity [103, 104].

8.5. Item Response Theory. After the factor structure of the SMC scale was determined by EFA and CFA, the item response theory (IRT) was used to assess the validity of items of the scale on the entire sample. The IRT analyses were carried out for each dimension separately. A graded response model was used in IRT analysis since it is suitable for a 5-point Likert scale like in our case. The item discrimination (α) and difficulty (β) scores were calculated, and the item characteristic curve (ICC) was examined. For the sake of clarity, an α value > 1.0 indicates that the item is strongly discriminant while the β provides an insight into the relationship between the latent trait and the specific response categories for the items. IRT results are shown in Table 3 and Figure 2.

According to Table 3, the item discrimination (α) values vary between 2.48 and 6.57 for the first factor (social media confidence) and 2.20 and 3.73 for the second one (social media connectedness). Therefore, it appears that the discrimination of all SMC items was high.

For items 1, 2, 3, and 4, the thresholds span the negative section of the factor. A score of 5 was the most probable for respondents above the zero latent factor level. Other options were more unlikely. This indicates that factor 1 items were “easy” ones to rate high. For this reason, F1-items were unable to differentiate between low and high factor-level respondents but only between the 4-score and 5-score participants. As for items 5, 6, and 8, their thresholds were more widely spread out. Thus, they can be considered “harder” items and so less likely to receive a concentration of high scores. The item characteristic curves (ICC) shown in Figure 2 presented an S-shaped curve as recommended.

8.6. Internal Consistency. The reliability analysis of the SMC two-factor model was carried out by calculating McDonald’s omega on the whole sample given the consensus in the psychometric literature that Cronbach’s alpha is rarely appropriate [105–107]. Nonetheless, since coefficient alpha is a special case of omega when alpha’s assumptions are

satisfied [108], we relied on alpha interpretation rules to discuss SMC reliability. For the sake of clarity, we specify that Cronbach’s alpha values can be classified as minimally acceptable ($\alpha = 0.65$), acceptable ($\alpha = 0.70$), and optimal ($\alpha = 0.80$) [109, 110]. Both SMC factors showed an optimal reliability (F1 (social media confidence) $\omega = 0.81$; F2 (social media connectedness) $\omega = 0.86$).

8.7. Item-Total Correlations. As an important phase of item analysis, the corrected item-factor total correlations were also examined on the whole sample to determine the coherency of items within the same factor. All item-factor total correlations were much greater than the threshold value of 0.30 [110, 111], ranging from 0.71 to 0.84 for the social media confidence and from 0.67 to 0.75 for the social media connectedness. These results suggested that the SMC scale has significant item-factor relationships.

9. Study 2

9.1. Method

9.1.1. Participants and Procedure. The SMC scale was administered in its final form (7 items), adjusted based on results of the previous study, alongside the Internet self-efficacy scale. This was done to test SMC convergent validity. Before proceeding with the recruitment phase, we performed the power analysis to define the required sample size for our research purposes. To do that, we used G*Power [112, 113]. Since the authors planned to rely on Pearson’s correlation to investigate the SMC relationship with Internet self-efficacy, a power analysis was computed for this type of analysis. The power analysis showed that a sample size of 1569 would be required to achieve a statistical power of 0.95 while being able to capture even a small effect size ($r = 0.10$) and assuming a significance level of 0.01. Moreover, since our study is mainly based on correlation, we accounted for the required sample size for achieving a stable measurement-error-free correlation. In our case (i.e., population correlation $\rho = 0.10$; composite score reliability derived from other works $\omega = 0.80$), a stable measurement-error-free correlation would be met at 380 [114]. Since our work is exploratory, the authors relied on a nonprobability method based on the voluntary census to test their hypotheses. Participation was promoted through posts and messages on social media platforms like Facebook and Instagram since being a social media user was requested to be eligible for participation. In the second study, 3100 people (74% females) participated and completed the survey. The participants had an average age of 29.51 (s.d. = 11.46; age range = 14–79). Data were collected following the Italian law’s privacy requirements (Law Decree DL-101/2018) and EU regulation (2016/679).

9.1.2. Measures. The Internet self-efficacy scale (ISS) consists of 17 items measured by a 7-point Likert-type scale ranging from 1 (not sure) to 7 (totally sure). The scale captures participants’ self-efficacy while performing several online activities of different complexity [54]. This scale revolves around five factors (reactive/generative self-efficacy, differentiating self-efficacy, organization self-efficacy,

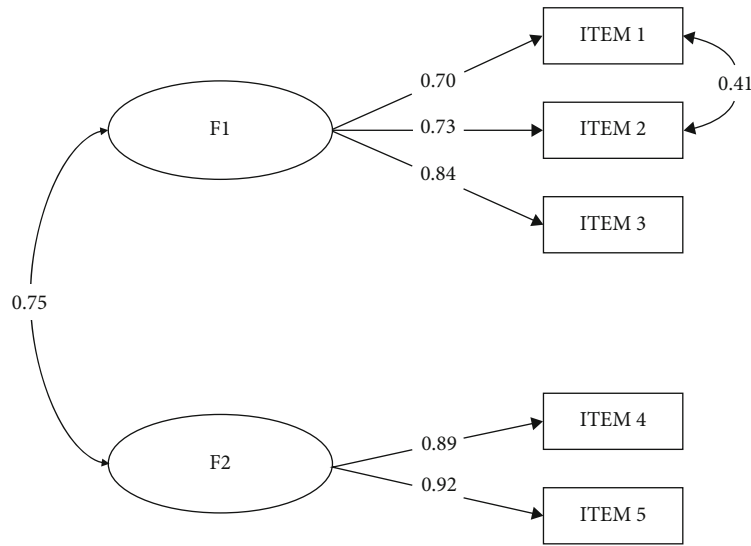


FIGURE 1: Results of confirmatory factor analysis of the two-factor model.

TABLE 3: Item response theory analysis.

Factor	Item	α	Z	p	β_1	β_2	β_3	β_4
F1	1	4.06	40.12	<0.001	-2.18	-1.50	-0.67	0.27
	2	6.57	24.00	<0.001	-2.02	-1.39	-0.55	0.36
	3	3.26	46.41	<0.001	-2.14	-1.27	-0.29	0.68
	4	2.48	44.46	<0.001	-2.65	-1.88	-0.82	0.32
F2	5	3.73	33.14	<0.001	-1.25	-0.37	0.51	1.33
	8	3.64	34.13	<0.001	-1.30	-0.44	0.38	1.32
		2.20	44.28	<0.001	-0.91	-0.05	0.81	1.86

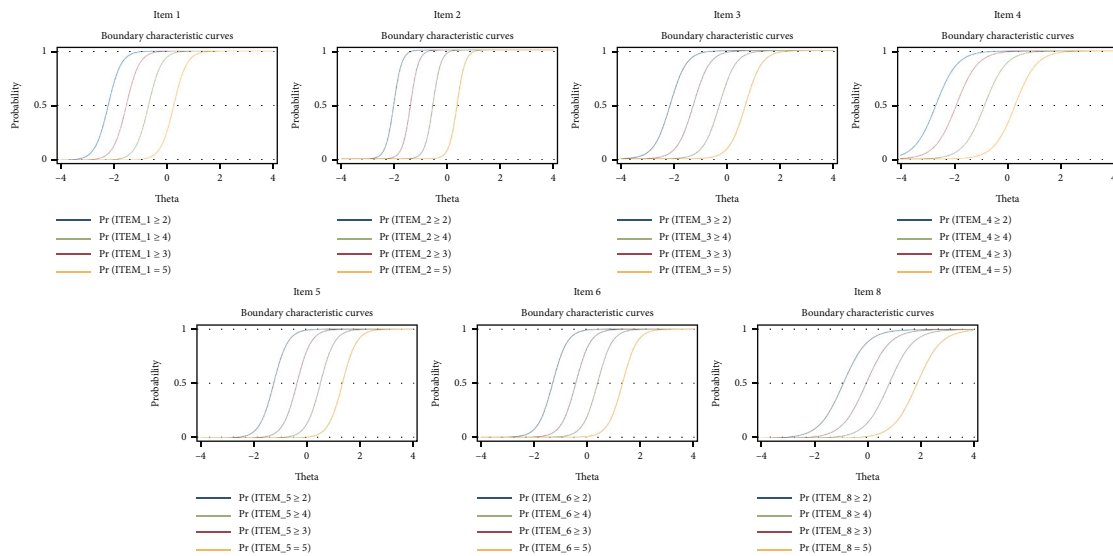


FIGURE 2: SMC item characteristic curves (ICCs). The curves describe the relationship between the probability $P(\theta)$ of choosing a category option in an item.

communication self-efficacy, search self-efficacy) and has a Cronbach's $\alpha = 0.91$.

9.1.3. Data Analysis. We first produced descriptive statistics for all the continuous variables collected. Then, we verified the preconditions necessary for Pearson correlation. For each Pearson correlation, we assessed the variables' normality through asymmetry and kurtosis values, homoscedasticity, and linearity. We also investigated gender-related differences through Welch's t -test since it performs better than Student's t -test whenever sample sizes and variances are unequal between groups and gives the same result when sample sizes and variances are equal [115]. Finally, we carried out Pearson correlation and partial correlation to assess SMC validity.

9.2. Results

9.2.1. Descriptive Statistics. First, we produced the descriptive statistics for all the scores involved in our validation process (Table 4).

9.3. Inferential Analyses. Subsequently, gender-related effects on SMC and ISS were investigated before proceeding with convergent validity analyses through Pearson's correlation. Thus, we compared males' and females' scores on SMC, ISS dimensions, and ISS total score through Welch's t -tests since sample sizes were unequal between groups. The analysis showed that gender did not affect SMC F2, ISS organization, and ISS communication, while marginally affected SMC F1 and ISS reactive/generative, differentiation, and search dimensions (Table 5). For the sake of clarity, we specify that a commonly used rule for Cohen's d interpretation distinguishes small, medium, and large effect sizes for d values of, respectively, 0.2, 0.5, and 0.8 based on benchmarks suggested by Cohen [116]. In our case, we observed gender-related differences that are equal to or below the threshold for small effects. Since gender did not seem to greatly affect the SMC and ISS variables, the researchers excluded gender from the subsequent validity analysis.

We then assessed the relationship that both SMC factors, ISS dimensions, and ISS total score entertained with age. In line with our expectations, age had negative statistically significant linear relationships with both SMC F1 ($r = -0.37$; $p < 0.001$) and SMC F2 ($r = -0.14$; $p < 0.001$), as well as with ISS (r ranging from -0.12 to -0.24 ; $p < 0.001$).

Finally, we carried out Pearson's correlation to assess if SMC factors were related to ISS dimensions and total score as expected. Since age resulted in influencing both SMC and ISS, we also ran partial correlations to investigate the relationship between SMC factors and ISS dimension net of age-related effect. As we can gather from Table 6, all ISS dimensions and ISS total score were statistically related to both SMC factors. The Pearson r coefficient can be interpreted considering values of 0.10, 0.20, and 0.30 as relatively small, typical, and relatively large [117]. In our case, all the correlations resulted as relatively large in terms of effect size with just one exception. Nonetheless, the correlation between ISS search and SMC F2 was still very close to the threshold for relatively large effect sizes

TABLE 4: Descriptive statistics of the scales used for social media capital validation.

Variables	Min	Max	Mean	s.d.
SMC F1	4	20	14.94	3.76
SMC F2	3	15	8.32	3.13
ISS reactive/generative	3	42	20.71	9.03
ISS differentiation	5	28	20.42	5.44
ISS organization	3	42	16.28	4.89
ISS communication	2	21	9.40	3.85
ISS search	2	14	70.73	2.76
ISS total	17	119	77.55	77.55

Note: $N = 3100$; s.d. = standard deviation; ISS = Internet self-efficacy scale; SMC = social media capital.

(i.e., $r = 0.28$). Notably, three of four ISS dimensions were more strongly correlated with the SMC first factor compared to the SMC second factor. The ISS total score also resulted in having a higher correlation with the SMC first factor. Just the ISS reactive/generative dimension appeared more strongly related with SMC F2 with respect to SMC F1.

10. Study 3

10.1. Methods

10.1.1. Participants. The SMC scale was once again administered in its final form (7 items), as in study 2. SMC external validity was evaluated by administering the SMC scale together with the Internet Motive Scale and Bergen Social Media Addiction Scale. The adequate sample size for study 3 was identified based on power analysis through the G* Power software [112, 113]. For Pearson correlation, the power analysis showed that a sample size of 211 would be required to achieve a statistical power of 0.90 assuming a typical effect size ($r = 0.20$) and a significance level of 0.05. As for the previous studies, the authors relied on volunteers to test their hypotheses. Participation was once again promoted through posts and messages on social media platforms to be able to reach social media users. In the third study, 244 people (60.7% females) participated and completed the survey. The participants had an average age of 26.65 (s.d. = 7.40; age range = 17-61). Italian law's requirements of privacy and informed consent (Law Decree DL-101/2018) and EU regulation (2016/679) were followed in our data collection procedure.

10.1.2. Measures. The Internet Motivation Scale (IMS) developed by Wolfradt and Doll [118] consists of twenty items measured on a 5-point rating scale (1 = completely disagree to 5 = completely agree), assessing the three motives regarding Internet usage: information (I use the Internet because of its current information), interpersonal communication (the Internet makes me feel like I am close to others), and entertainment (the Internet helps me in passing my time). The internal consistencies of the three motives are as follows: 0.84 for information, 0.81 for interpersonal communication, and 0.76 for entertainment.

TABLE 5: Welch's *t*-test results on gender-related differences in SNC and ISS.

Variable	Gender	<i>M</i>	s.d.	<i>t</i>	df	<i>p</i>	Cohen's <i>d</i>
SMC F1	Males	14.49	3.91	-3.88	1339.01	<0.001	-0.16
	Females	15.10	3.69				
SMC F2	Males	8.25	3.03	-0.70	1468.43	0.48	n.c.
	Females	8.34	3.17				
ISS reactive/generative	Males	20.01	9.10	-2.54	1397.02	0.01	-0.10
	Females	20.96	9.00				
ISS differentiation	Males	20.00	5.68	-2.52	1337.72	0.01	-0.10
	Females	20.57	5.34				
ISS organization	Males	16.28	5.09	0.01	1346.03	0.99	n.c.
	Females	16.28	4.82				
ISS communication	Males	9.36	4.09	-0.36	1316.82	0.72	n.c.
	Females	9.42	3.77				
ISS search	Males	10.29	2.80	-5.27	1369.28	<0.001	-0.20
	Females	10.88	2.71				
ISS total	Males	75.94	20.16	-2.63	1408.86	0.009	-0.11
	Females	78.11	20.16				

Note: *N* = 3100; s.d. = standard deviation; ISS = Internet self-efficacy scale; SMC = social media capital; n.c. = not computed due to nonstatistically significant result.

TABLE 6: Correlation matrix. Pearson's correlation and partial correlation values between social media capital factors and validity measures are reported.

Convergent validity measures	SMC F1	SMC F2	SMC F1 (controlled for age)	SMC F2 (controlled for age)
ISS reactive/generative	0.34***	0.40***	0.32***	0.39***
ISS differentiation	0.43***	0.35***	0.40***	0.33***
ISS organization	0.46***	0.35***	0.42***	0.33***
ISS communication	0.51***	0.42***	0.47***	0.40***
ISS search	0.41***	0.28***	0.38***	0.26***
ISS total	0.51***	0.45***	0.50***	0.46***

Note: *N* = 3100; ****p* < 0.001.

The Bergen Social Media Addiction Scale (BSMAS) [119] is a 6-item scale assessing problematic social media use with a 5-point Likert scale (from "never" to "always") yielding a composite score from 6 to 30. The scale asks to indicate how often "You feel an urge to use social media more and more" or "You have tried to cut down on the use of social media without success". BSMAS is a one-factor solution scale and was adapted from the previous "Bergen Facebook Addiction Scale" [120]. The measure has shown acceptable psychometric properties and has a good internal consistency (Cronbach's alpha = 0.88).

10.1.3. Data Analysis. In the same way as study 2, we produced descriptive statistics for the continuous variables and then performed Pearson correlation and partial correlation after checking for assumptions and possible gender-related differences through Welch's *t*-test.

10.2. Results

10.2.1. Descriptive Statistics. Descriptive statistics were computed for all the scores involved in our external validation process (Table 7).

10.2.2. Inferential Analyses. As in study 2, we first analyzed whether gender and age affected the variables that the authors intended to subsequently investigate through Pearson's correlation. The analyses conducted through Welch's *t*-tests suggested the absence of gender-related effects on all the variables included in our data collection except for SMC factor 1 ($t_{(214.08)} = -2.05$; $p = 0.041$; Cohen's $d = 0.25$). In line with what was already reported in study 2 results, gender-related differences for SMC F1 appeared small. Age resulted correlated with SMC F1 ($r = -0.27$; $p < 0.001$) but not with SMC F2 ($r = 0.03$; $p = 0.65$). Age did not affect Internet motivations but entertained a negative small relationship with social media addiction ($r = -0.15$; $p < 0.02$).

Given these results, we decided to consider age but not gender as a possible confounding variable to control for in subsequent analyses. Therefore, we computed both Pearson's correlation and partial correlation to assess the relationship between SMC factors, Internet motivations, and social media addiction. As we can gather from Table 8, both Internet motives and social media addiction were statistically related to both SMC factors. Notably, SMC F2 appeared to have typically large correlation values with all

TABLE 7: Descriptive statistics of the scales used for social media capital external validation.

Variables	Min	Max	Mean	s.d.
SMC F1	4	20	16.27	3.57
SMC F2	3	15	8.84	3.31
IMS information motive	13	40	28.32	4.96
IMS interpersonal communication motive	7	31	17.75	5.43
IMS entertainment motive	5	25	16.17	3.76
BSMAS	6	30	13.43	5.35

Note: $N = 244$; s.d. = standard deviation; IMS = Internet Motive Scale; SMC = social media capital; BSMAS = Bergen Social Media Addiction Scale.

TABLE 8: Correlation matrix. Pearson's correlation and partial correlation values between social media capital factors and external validity measures are reported.

External validity measures	SMC F1	SMC F2	SMC F1 (controlled for age)	SMC F2 (controlled for age)
IMS information motive	0.19**	0.31***	0.20**	0.31***
IMS interpersonal communication motive	0.36***	0.53***	0.36***	0.53***
IMS entertainment motive	0.20**	0.32***	0.18**	0.33***
BSMAS	0.32***	0.32***	0.29***	0.33***

Note: $N = 3100$; *** $p < 0.001$; ** $p < 0.01$; IMS = Internet Motive Scale; SMC = social media capital; BSMAS = Bergen Social Media Addiction Scale.

Internet motives. Moreover, SMC F2 always showed higher correlation coefficients with Internet motives than SMC F1. As expected, SMC F2 had the highest correlation value for the interpersonal communication motive. Finally, both SMC factors entertained large and similar correlations with social media addiction.

11. Discussion

Nowadays, social media is a social environment that is always at hand (i.e., ubiquitous and pervasive), with which human beings can satisfy some social needs. These include, for example, cultivating one's own social capital [18–20], which is an important thing for a series of reasons. For instance, social capital may affect in a positive way of people's well-being [121, 122] and self-efficacy [123], in real life as well as in virtual environments [68, 74, 124]. However, to fully access the potential of virtual environments for expanding one's online social capital, it requires a certain degree of competence and fluency in the use of ICTs. As the literature reported, Internet self-efficacy has a positive impact on cultivating social capital online [48].

For these reasons, we decided to develop a tool aimed at measuring social capital on social media (SMC) that includes both these aspects (i.e., social media confidence and fluency and social connection with others via social media). Our instrument was made by joining items from two already existing scales, one for each construct, and then its psychometric properties were analyzed.

Following the exploratory factor analysis, we removed item 7 (i.e., concerning the increased connection with the family due to social media) from the initial pool of 8 items. This is in line with several studies suggesting that online bridging social capital tends to develop more than

the bonding one. Way more than to deepen relationships with family members (that is bonding capital), social media sites tend to be used to cultivate a network of weak ties with people who share similar interests, characteristics, and life situations [19, 21, 22].

The scale in its final 7-item version has a two-factor factorial structure confirmed by the fit indices of the confirmatory factor analysis, exactly as assumed during the development of the instrument. All items appeared to perform adequately even though factor 1 items were "easy" ones to rate high; this probably due to the young age and consequent high literacy with social media of the sample [125–127]. The reliability was also found to be optimal (i.e., > 0.80) for both dimensions of the SMC.

Finally, the relationships that SMC entertained with ISS, IMS, and BSMAS shown in studies 2 and 3 reassured about the external validity of the SMC scale. More specifically, in our second study, both factors of the SMC were found to be significantly correlated with all ISS subscales, with a moderate to high effect size (the only exception being the correlation between factor 2 and ISS "search", which was just below the 0.30 cut-off value). As expected, a stronger sense of self-efficacy in using the Internet, in any of its forms, is associated with a higher confidence in one's ability to use social media too, as well as with the fact of employing them to nurture one's social capital. This can be explained due to the fact that, as utterly trivial as it may sound, social media sites are Internet-based. Therefore, ease, comfort, and confidence with them should imply a certain degree of familiarity with the online environment. The same should apply to the sense of being capable of increasing one's bridging capital via social media, thus through the Internet.

Our third study, instead, took into consideration two other aspects, namely, individual motives when approaching

the Internet and the tendency towards social media addiction. Significant correlations were observed between both SMC factors and all scales.

As regards the former, all correlations with factor 2 ranged from moderate to strong, whereas those with factor 1 were weaker, though significant. The “communication motive” was the most associated with both, which is in line with what was expected. In fact, the more individuals are motivated to use the Internet to communicate with other people, the more they should be drawn towards social media sites and, even more prominently, to employ them to strengthen their social connections. Information and entertainment-seeking motives are not as central in this sense, although they certainly do not draw attention from social media sites: rather they contribute to their appeal to a lower degree.

SMC external validity has also been tested against the BSMAS scale. Indeed, we expected the two measures to be positively correlated, given how higher levels of social media addiction imply by definition a conspicuous amount of time spent on these sites, thus a higher self-efficacy in their usage, often with the purpose of forming and maintaining social relationships [128–131]. The same relation should not be so strict in the opposite direction, though, in the sense that using social media sites confidently and/or in order to cultivate personal relationships do not necessarily imply addiction, the reason why the relations between variables were expected to be limited in size.

Our results were in line with our hypotheses, as SMC factors were positively and moderately correlated to BSMAS but only explained 9.73% of its variance each: although related, these constructs are for the most part distinct from one another.

The SMC appears to be a valid tool to measure individual confidence in using social media and in employing them to maintain and develop one’s social capital. As social media have an increasingly central role in driving social interaction and connecting people, it is fundamental to be able to assess the degree to which individuals are able to capitalize on them in order to cultivate significant interpersonal relationships, thus fostering their well-being.

This could be particularly useful, for example, in those situations in which the possibility to have face-to-face interaction is limited, as it has been the case during the pandemic or for hospitalized people.

Our studies are not without limitations, the main one being the use of convenience samples. Although this is common practice in psychological literature, it poses problems as regards result generalization. Our samples, despite the size, mainly consist of young people in their twenties and are disproportionately composed of women (75.4% in study 1, 74% in study 2, 60.7% in study 3). This means we should be cautious in interpreting our results as they might not accurately represent the general population.

Data Availability

Data could be available upon request by contacting the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

- [1] A. M. Kaplan and M. Haenlein, “Users of the world, unite! The challenges and opportunities of Social Media,” *Business horizons*, vol. 53, no. 1, pp. 59–68, 2010.
- [2] S. A. Brasel and J. Gips, “Media multitasking behavior: Concurrent television and computer usage,” *Cyberpsychology, Behavior, and Social Networking*, vol. 14, no. 9, pp. 527–534, 2011.
- [3] L. F. Bright, S. B. Kleiser, and S. L. Grau, “Too much Facebook? An exploratory examination of social media fatigue,” *Computers in Human Behavior*, vol. 44, pp. 148–155, 2015.
- [4] H. G. de Zúñiga, M. Barnidge, and A. Scherman, “Social media social capital, offline social capital, and citizenship: exploring asymmetrical social capital effects,” *Political Communication*, vol. 34, no. 1, pp. 44–68, 2017.
- [5] T. Ryan, K. A. Allen, D. L. Gray, and D. M. McInerney, “How social are social media? A review of online social behaviour and connectedness,” *Journal of Relationships Research*, vol. 8, 2017.
- [6] H. T. Chen and X. Li, “The contribution of mobile social media to social capital and psychological well-being: examining the role of communicative use, friending and self-disclosure,” *Computers in Human Behavior*, vol. 75, pp. 958–965, 2017.
- [7] Y. Lu, T. Pan, and S. Deng, “What drives patients affected by depression to share in online depression communities? A social capital perspective,” *Healthcare (Basel, Switzerland)*, vol. 7, no. 4, pp. 133–E133, 2019.
- [8] N. Misirlis, M. H. Zwaan, and D. Weber, “International students’ loneliness, depression and stress levels in COVID-19 crisis. The role of social media and the host university,” 2020, <https://arxiv.org/abs/2005.12806>.
- [9] B. Neves, J. R. Fonseca, F. Amaro, and A. Pasqualotti, “Social capital and internet use in an age-comparative perspective with a focus on later life,” *PLoS One*, vol. 13, no. 2, article e0192119, 2018.
- [10] J. H. Yoo and E. J. Jeong, “Psychosocial effects of SNS use: a longitudinal study focused on the moderation effect of social capital,” *Computers in Human Behavior*, vol. 69, pp. 108–119, 2017.
- [11] G. Brown and P. M. Greenfield, “Staying connected during stay-at-home: communication with family and friends and its association with well-being,” *Human Behavior and Emerging Technologies*, vol. 3, no. 1, pp. 147–156, 2021.
- [12] A. Guazzini, A. Pesce, L. Marotta, and M. Duradoni, “Through the second wave: analysis of the psychological and perceptive changes in the Italian population during the COVID-19 pandemic,” *International Journal of Environmental Research and Public Health*, vol. 19, no. 3, p. 1635, 2022.
- [13] R. Sigurvinsdottir, I. E. Thorisdottir, and H. F. Gylfason, “The impact of COVID-19 on mental health: the role of locus on control and Internet use,” *International Journal of Environmental Research and Public Health*, vol. 17, no. 19, p. 6985, 2020.
- [14] B. K. Wiederhold, “Using social media to our advantage: alleviating anxiety during a pandemic,” *Cyberpsychology, Behavior and Social Networking*, vol. 23, no. 4, pp. 197–198, 2020.

- [15] L. Zhu, "The psychology behind video games during COVID-19 pandemic: a case study of animal crossing: new horizons," *Human Behavior and Emerging Technologies*, vol. 3, no. 1, pp. 157–159, 2021.
- [16] P. Bourdieu, "The forms of capital," in *Handbook of Theory and Research for the Sociology of Education*, J. G. Richardson, Ed., pp. 241–258, Greenwood Press, New York, 1986.
- [17] R. D. Putnam, "Bowling alone: America's declining social capital," *Journal of Democracy*, vol. 6, no. 1, pp. 65–78, 1995.
- [18] A. Bohn, C. Buchta, K. Hornik, and P. Mair, "Making friends and communicating on Facebook: implications for the access to social capital," *Social Networks*, vol. 37, pp. 29–41, 2014.
- [19] N. B. Ellison, C. Steinfield, and C. Lampe, "The benefits of Facebook "friends": social capital and college students' use of online social network sites," *Journal of Computer-Mediated Communication*, vol. 12, no. 4, pp. 1143–1168, 2007.
- [20] J. Vitak, N. B. Ellison, and C. Steinfield, "The ties that bond: re-examining the relationship between Facebook use and bonding social capital," in *2011 44th Hawaii International Conference on System Sciences*, pp. 1–10, Kauai, HI, USA, 2011.
- [21] J. Donath and D. Boyd, "Public displays of connection," *BT Technology Journal*, vol. 22, no. 4, pp. 71–82, 2004.
- [22] C. Steinfield, N. B. Ellison, and C. Lampe, "Social capital, self-esteem, and use of online social network sites: a longitudinal analysis," *Journal of Applied Developmental Psychology*, vol. 29, no. 6, pp. 434–445, 2008.
- [23] P. B. Brandtzaeg, "Towards high-speed social relationships: a longitudinal study of Facebook use," in *International conference on Ehealth*, pp. 86–96, Lisbon, Portugal, 2014.
- [24] P. B. Brandtzaeg, M. Lüders, and J. H. Skjetne, "Too many Facebook "friends"? Content sharing and sociability versus the need for privacy in social network sites," *International Journal of Human-Computer Interaction*, vol. 26, no. 11–12, pp. 1006–1030, 2010.
- [25] M. D. Hossain and A. S. Veenstra, "Social capital and relationship maintenance: uses of social media among the South Asian diaspora in the U.S.," *Asian Journal of Communication*, vol. 27, no. 1, pp. 1–17, 2017.
- [26] J. R. Williams, "The use of online social networking sites to nurture and cultivate bonding social capital: a systematic review of the literature from 1997 to 2018," *New Media & Society*, vol. 21, no. 11–12, pp. 2710–2729, 2019.
- [27] C.-H. Jin, "The role of Facebook users' self-systems in generating social relationships and social capital effects," *New Media & Society*, vol. 17, pp. 501–519, 2013.
- [28] J. Cho, "Roles of smartphone app use in improving social capital and reducing social isolation," *Cyberpsychology, Behavior and Social Networking*, vol. 18, no. 6, pp. 350–355, 2015.
- [29] C. E. Tabo, *Social Media Use and Depression: The Mediating Role of Public Self-Awareness*, 2020.
- [30] C. E. Beaudoin and C. C. Tao, "Benefiting from social capital in online support groups: an empirical study of cancer patients," *Cyberpsychology & Behavior*, vol. 10, no. 4, pp. 587–590, 2007.
- [31] L. Zhao, C. Liang, and D. Gu, "Mobile social media use and trailing parents' life satisfaction: social capital and social integration perspective," *The International Journal of Aging and Human Development*, vol. 92, no. 3, pp. 383–405, 2021.
- [32] A. Masciantonio, D. Bourguignon, P. Bouchat, M. Balty, and B. Rimé, "Don't put all social network sites in one basket: Facebook, Instagram, Twitter, TikTok, and their relations with well-being during the COVID-19 pandemic," *PLoS One*, vol. 16, no. 3, article e0248384, 2021.
- [33] L. Y. Yang, "Influence of social short videos on social capital of college students based on experimental analysis," in *2021 2nd International Conference on Information Science and Education (ICISE-IE)*, pp. 801–805, Chongqing, China, 2021.
- [34] M. Burke, R. Kraut, and C. Marlow, "Social capital on Facebook: differentiating uses and users," in *Proceedings of the SIGCHI Conference on Human Factors in Computing. ACM (2011)*, pp. 571–580, Vancouver in British Columbia, Canada, 2011.
- [35] Y. Liu, J. Venkatanathan, J. Goncalves, E. Karapanos, and V. Kostakos, "Modeling what friendship patterns on Facebook reveal about personality and social capital," *ACM Transactions on Computer-Human Interaction (TOCHI)*, vol. 21, no. 3, pp. 1–20, 2014.
- [36] S. S. Kahai and Y. Lei, "Building social capital with Facebook: type of network, availability of other media, and social self-efficacy matter," *International Journal of Human-Computer Studies*, vol. 130, pp. 113–129, 2019.
- [37] B. R. McKneely, J. Kim, X. Leung, and S. Pookulangara, "Social capital on Instagram: application for small apparel retailers," *Journal of Marketing Development and Competitiveness*, vol. 14, no. 4, pp. 22–38, 2020.
- [38] T. Daugherty, M. Eastin, and H. Gangadharbatla, "e-CRM: understanding Internet confidence and implications for customer relationship management," in *Advances in Electronic Marketing*, I. Clark and T. Flaherty, Eds., pp. 67–82, James Madison University, Idea Group Publishing, Inc, 2005.
- [39] J. L. Wang, L. A. Jackson, H. Z. Wang, and J. Gaskin, "Predicting social networking site (SNS) use: personality, attitudes, motivation and Internet self-efficacy," *Personality and Individual Differences*, vol. 80, pp. 119–124, 2015.
- [40] A. Bandura, "Self-efficacy mechanism in human agency," *American Psychologist*, vol. 37, no. 2, pp. 122–147, 1982.
- [41] A. Bandura, "Self-efficacy: the foundation of agency," in *Control of Human Behavior, Mental Processes, and Consciousness: Essays in Honor of the 60th Birthday of August Flammer*, W. J. Perrig and A. Grob, Eds., pp. 16–30, Taylor & Francis Inc, 2000.
- [42] S. C. Chuang, F. M. Lin, and C. C. Tsai, "An exploration of the relationship between internet self-efficacy and sources of internet self-efficacy among Taiwanese university students," *Computers in Human Behavior*, vol. 48, pp. 147–155, 2015.
- [43] M. Igarria and J. Iivari, "The effects of self-efficacy on computer usage," *Omega*, vol. 23, no. 6, pp. 587–605, 1995.
- [44] M. Duradoni, G. Salvatori, S. Meacci, G. Panerai, and A. Guazzini, *Development and Validation of the Internet Locus of Control Scale (I-LOC)*, New Media & Society, 2021.
- [45] M. S. Eastin and R. LaRose, "Internet self-efficacy and the psychology of the digital divide," *Journal of Computer-Mediated Communication*, vol. 6, no. 1, article JCMC611, 2000.
- [46] H. Gangadharbatla, "Facebook me: collective self-esteem, need to belong, and internet self-efficacy as predictors of the iGeneration's attitudes toward social networking sites," *Journal of Interactive Advertising*, vol. 8, no. 2, pp. 5–15, 2008.
- [47] N. Park, H. S. Oh, and N. Kang, "Factors influencing intention to upload content on Wikipedia in South Korea: the

- effects of social norms and individual differences,” *Computers in Human Behavior*, vol. 28, no. 3, pp. 898–905, 2012.
- [48] F. Zheng, N. A. Khan, and S. Hussain, “The COVID 19 pandemic and digital higher education: exploring the impact of proactive personality on social capital through internet self-efficacy and online interaction quality,” *Children and Youth Services Review*, vol. 119, article 105694, 2020.
- [49] P. L. Teh, J. S. Y. Ho, C. C. Yong, and S. Y. Yew, “Does Internet self-efficacy affect knowledge sharing behavior?,” in *2010 IEEE International Conference on Industrial Engineering and Engineering Management*, Macao, China, 2010.
- [50] M. M. Sharabati, “The impact of knowledge sharing through Facebook on students’ academic performance in Palestine,” *International Journal of Business and Information*, vol. 13, no. 2, pp. 155–190, 2018.
- [51] E. Hargittai, A. M. Piper, and M. R. Morris, “From Internet access to internet skills: digital inequality among older adults,” *Universal Access in the Information Society*, vol. 18, no. 4, pp. 881–890, 2019.
- [52] B. B. Neves, “Does the Internet matter for strong ties? Bonding social capital, Internet use, and age-based inequality,” *International Review of Sociology*, vol. 25, no. 3, pp. 415–433, 2015.
- [53] B. B. Neves and J. R. Fonseca, “Latent class models in action: bridging social capital & internet usage,” *Social Science Research*, vol. 50, pp. 15–30, 2015.
- [54] Y. Kim and M. Glassman, “Beyond search and communication: development and validation of the Internet self-efficacy scale (ISS),” *Computers in Human Behavior*, vol. 29, no. 4, pp. 1421–1429, 2013.
- [55] R. Alnjadat, M. M. Hmaid, T. E. Samha, M. M. Kilani, and A. M. Hasswan, “Gender variations in social media usage and academic performance among the students of University of Sharjah,” *Journal of Taibah University medical sciences*, vol. 14, no. 4, pp. 390–394, 2019.
- [56] H. Krasnova, N. F. Veltri, N. Eling, and P. Buxmann, “Why men and women continue to use social networking sites: the role of gender differences,” *The Journal of Strategic Information Systems*, vol. 26, no. 4, pp. 261–284, 2017.
- [57] R. LaRose, C. A. Lin, and M. S. Eastin, “Unregulated Internet usage: addiction, habit, or deficient self-regulation?,” *Media Psychology*, vol. 5, no. 3, pp. 225–253, 2003.
- [58] J. D. Shapka, “Adolescent technology engagement: it is more complicated than a lack of self-control,” *Human Behavior and Emerging Technologies*, vol. 1, no. 2, pp. 103–110, 2019.
- [59] S. Sun, “An examination of disposition, motivation, and involvement in the new technology context computers in human behavior,” *Computers in Human Behavior*, vol. 24, no. 6, pp. 2723–2740, 2008.
- [60] F. Bánya, Á. Zsila, O. Király et al., “Problematic social media use: results from a large-scale nationally representative adolescent sample,” *PLoS One*, vol. 12, no. 1, article e0169839, 2017.
- [61] D. Brevers and O. Turel, “Strategies for self-controlling social media use: classification and role in preventing social media addiction symptoms,” *Journal of Behavioral Addictions*, vol. 8, no. 3, pp. 554–563, 2019.
- [62] H. Fidan, “Development and validation of the mobile addiction scale: the components model approach,” *Addicta: The Turkish Journal on Addictions*, vol. 3, no. 3, pp. 452–469, 2016.
- [63] M. Kwon, D. J. Kim, H. Cho, and S. Yang, “The smartphone addiction scale: development and validation of a short version for adolescents,” *PLoS One*, vol. 8, no. 12, article e83558, 2013.
- [64] F. P. B. Mota and I. Cilento, “Competence for internet use: integrating knowledge, skills, and attitudes,” *Computers and Education Open*, vol. 1, article 100015, 2021.
- [65] M. J. Tsai and C. C. Tsai, “Junior high school students’ Internet usage and self-efficacy: a re-examination of the gender gap,” *Computers & Education*, vol. 54, no. 4, pp. 1182–1192, 2010.
- [66] J. A. Roberts and M. E. David, “The social media party: fear of missing out (FoMO), social media intensity, connection, and well-being,” *International Journal of Human-Computer Interaction*, vol. 36, no. 4, pp. 386–392, 2020.
- [67] H. Hwang and K. O. Kim, “Social media as a tool for social movements: the effect of social media use and social capital on intention to participate in social movements,” *International Journal of Consumer Studies*, vol. 39, no. 5, pp. 478–488, 2015.
- [68] D. H. Choi and G. Y. Noh, “The influence of social media use on attitude toward suicide through psychological well-being, social isolation, and social support,” *Information, Communication & Society*, vol. 23, no. 10, pp. 1427–1443, 2020.
- [69] D. M. Haslam, A. Tee, and S. Baker, “The use of social media as a mechanism of social support in parents,” *Journal of Child and Family Studies*, vol. 26, no. 7, pp. 2026–2037, 2017.
- [70] H. Pang, “Examining associations between university students’ mobile social media use, online self-presentation, social support and sense of belonging,” *Aslib Journal of Information Management*, vol. 72, no. 3, pp. 321–338, 2020.
- [71] S. Kocdar, A. Karadeniz, and N. Goksel, “Using Facebook for leveraging sense of community in self-paced open and distance learning courses,” *International Journal of Emerging Technologies in Learning (iJET)*, vol. 13, no. 5, pp. 100–116, 2018.
- [72] D. Paton and M. Irons, “Communication, sense of community, and disaster recovery: a Facebook case study,” *Frontiers in communication*, vol. 1, pp. e4–e4, 2016.
- [73] E. B. O’Day and R. G. Heimberg, “Social media use, social anxiety, and loneliness: a systematic review,” *Computers in Human Behavior Reports*, vol. 3, article 100070, 2021.
- [74] M. Pittman, “Happiness, loneliness, and social media: perceived intimacy mediates the emotional benefits of platform use,” *The Journal of Social Media in Society*, vol. 7, no. 2, pp. 164–176, 2018.
- [75] M. T. Abassi Shavazi and P. Homayoon, “Social media and social isolation: a study of relationship between new communication technologies and social isolation,” *Quarterly of Cultural Studies & Communication*, vol. 10, no. 36, pp. 43–66, 2014.
- [76] B. A. Primack, A. Shensa, C. G. Escobar-Viera et al., “Use of multiple social media platforms and symptoms of depression and anxiety: a nationally-representative study among U.S. young adults,” *Computers in Human Behavior*, vol. 69, pp. 1–9, 2017.
- [77] B. A. Primack, S. A. Karim, A. Shensa, N. Bowman, J. Knight, and J. E. Sidani, “Positive and negative experiences on social media and perceived social isolation,” *American Journal of Health Promotion*, vol. 33, no. 6, pp. 859–868, 2019.
- [78] S. S. Tirukkovalluri, K. Malarvannan, R. C. Karthik, B. S. Mahendiran, and B. Arumugam, “An observational

- exploration of factors affecting perceived social isolation among social media using medical professional course students in south Indian state of India,” *Indian Journal of Community Health*, vol. 32, no. 1, pp. 76–81, 2020.
- [79] R. K. Merton, “The Matthew effect in science,” *Science*, vol. 159, no. 3810, pp. 56–63, 1968.
- [80] A. Ali, H. Wang, and A. N. Khan, “Mechanism to enhance team creative performance through social media: a transactive memory system approach,” *Computers in Human Behavior*, vol. 91, pp. 115–126, 2019.
- [81] G. Torkzadeh and T. P. Van Dyke, “Development and validation of an Internet self-efficacy scale,” *Behaviour & Information Technology*, vol. 20, no. 4, pp. 275–280, 2001.
- [82] T. Sun, S. Youn, G. Wu, and M. Kuntaraporn, “Online word-of-mouth (or mouse): an exploration of its antecedents and consequences,” *Journal of Computer-Mediated Communication*, vol. 11, no. 4, pp. 1104–1127, 2006.
- [83] Graphic, Visualization, & Usability Center, *The 10th WWW user survey conducted by the Graphic, Visualization, & Usability Center at Georgia Institute of Technology. Disponible*, 1998, https://www.cc.gatech.edu/gvu/user_surveys/survey-1998-10/.
- [84] J. C. de Winter, D. Dodou, and P. A. Wieringa, “Exploratory factor analysis with small sample sizes,” *Multivariate Behavioral Research*, vol. 44, no. 2, pp. 147–181, 2009.
- [85] A. L. Comrey, “Factor-analytic methods of scale development in personality and clinical psychology,” *Journal of Consulting and Clinical Psychology*, vol. 56, no. 5, pp. 754–761, 1988.
- [86] R. B. Cattell, “The scree test for the number of factors,” *Multivariate Behavioral Research*, vol. 1, no. 2, pp. 245–276, 1966.
- [87] H. F. Kaiser, “The application of electronic computers to factor analysis,” *Educational and Psychological Measurement*, vol. 20, no. 1, pp. 141–151, 1960.
- [88] E. Ferguson and T. Cox, “Exploratory factor analysis: a users’ guide,” *International Journal of Selection and Assessment*, vol. 1, no. 2, pp. 84–94, 1993.
- [89] A. B. Costello and J. Osborne, “Best practices in exploratory factor analysis: four recommendations for getting the most from your analysis,” *Practical assessment, research, and evaluation*, vol. 10, no. 7, pp. 1–9, 2005.
- [90] W. F. Velicer and D. N. Jackson, “Component analysis versus common factor analysis: some issues in selecting an appropriate procedure,” *Multivariate Behavioral Research*, vol. 25, no. 1, pp. 1–28, 1990.
- [91] W. R. Zwick and W. F. Velicer, “Comparison of five rules for determining the number of components to retain,” *Psychological Bulletin*, vol. 99, no. 3, pp. 432–442, 1986.
- [92] B. P. O’Connor, “SPSS and SAS programs for determining the number of components using parallel analysis and Velicer’s MAP test,” *Behavior Research Methods, Instruments, & Computers*, vol. 32, no. 3, pp. 396–402, 2000.
- [93] K. G. Jöreskog, “A general approach to confirmatory maximum likelihood factor analysis,” *Psychometrika*, vol. 34, no. 2, pp. 183–202, 1969.
- [94] L. R. Tucker and C. Lewis, “A reliability coefficient for maximum likelihood factor analysis,” *Psychometrika*, vol. 38, no. 1, pp. 1–10, 1973.
- [95] P. M. Bentler, “Comparative fit indexes in structural models,” *Psychological Bulletin*, vol. 107, no. 2, pp. 238–246, 1990.
- [96] P. M. Bentler, *EQS Structural Equations Program Manual*, vol. 6, Multivariate software, 1995.
- [97] M. W. Browne and R. Cudeck, “Alternative ways of assessing model fit,” in *Testing Structural Equation Models*, K. A. Bollen and J. S. Long, Eds., pp. 136–162, Sage, 1993.
- [98] B. M. Byrne, *Structural Equation Modeling with Mplus: Basic Concepts, Applications, and Programming*, Routledge, 2013.
- [99] L. T. Hu and P. M. Bentler, “Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives,” *Structural Equation Modeling: A Multidisciplinary Journal*, vol. 6, no. 1, pp. 1–55, 1999.
- [100] F. F. Chen, “Sensitivity of goodness of fit indexes to lack of measurement invariance,” *Structural Equation Modeling: A Multidisciplinary Journal*, vol. 14, no. 3, pp. 464–504, 2007.
- [101] G. W. Cheung and R. B. Rensvold, “Testing factorial invariance across groups: a reconceptualization and proposed new method,” *Journal of Management*, vol. 25, no. 1, pp. 1–27, 1999.
- [102] A. W. Meade, E. C. Johnson, and P. W. Braddy, “Power and sensitivity of alternative fit indices in tests of measurement invariance,” *Journal of Applied Psychology*, vol. 93, no. 3, pp. 568–592, 2008.
- [103] Y. Y. Hsiao and M. H. Lai, “The impact of partial measurement invariance on testing moderation for single and multi-level data,” *Frontiers in Psychology*, vol. 9, p. 740, 2018.
- [104] R. J. Vandenberg and C. E. Lance, “A review and synthesis of the measurement invariance literature: suggestions, practices, and recommendations for organizational research,” *Organizational Research Methods*, vol. 3, no. 1, pp. 4–70, 2000.
- [105] T. J. Dunn, T. Baguley, and V. Brunnsden, “From alpha to omega: a practical solution to the pervasive problem of internal consistency estimation,” *British Journal of Psychology*, vol. 105, no. 3, pp. 399–412, 2014.
- [106] A. F. Hayes and J. J. Coutts, “Use omega rather than Cronbach’s alpha for estimating reliability. But...,” *Communication Methods and Measures*, vol. 14, no. 1, pp. 1–24, 2020.
- [107] M. W. Watkins, “The reliability of multidimensional neuropsychological measures: from alpha to omega,” *The Clinical Neuropsychologist*, vol. 31, no. 6-7, pp. 1113–1126, 2017.
- [108] R. P. McDonald, *Test Theory: A Unified Treatment*, Psychology Press, 2013.
- [109] R. F. DeVellis, *Guidelines in Scale Development*, Scale development: Theory and applications, 1991.
- [110] J. C. Nunnally and I. H. Bernstein, “Validity,” *Psychometric theory*, vol. 3, pp. 99–132, 1994.
- [111] J. Pallant, “Survival manual,” in *A step by step guide to data analysis using SPSS*, Open University Press, 2011.
- [112] F. Faul, E. Erdfelder, A. Buchner, and A.-G. Lang, “Statistical power analyses using G*Power 3.1: tests for correlation and regression analyses,” *Behavior Research Methods*, vol. 41, no. 4, pp. 1149–1160, 2009.
- [113] F. Faul, E. Erdfelder, A.-G. Lang, and A. Buchner, “G*Power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences,” *Behavior Research Methods*, vol. 39, no. 2, pp. 175–191, 2007.
- [114] A. Kretschmar and G. E. Gignac, “At what sample size do latent variable correlations stabilize,” *Journal of Research in Personality*, vol. 80, pp. 17–22, 2019.
- [115] M. Delacre, D. Lakens, and C. Leys, “Why Psychologists Should by Default Use Welch’s t-test Instead of Student’s

- test,” *International Review of Social Psychology*, vol. 30, no. 1, pp. 92–101, 2017.
- [116] J. Cohen, *Statistical power analysis for the behavioral sciences*, Academic Press, New York, Rev. ed edition, 1977, <https://trove.nla.gov.au/version/45429781>.
- [117] G. E. Gignac and E. T. Szodorai, “Effect size guidelines for individual differences researchers,” *Personality and Individual Differences*, vol. 102, pp. 74–78, 2016.
- [118] U. Wolfradt and J. Doll, “Motives of adolescents to use the Internet as a function of personality traits, personal and social factors,” *Journal of Educational Computing Research*, vol. 24, no. 1, pp. 13–27, 2001.
- [119] C. S. Andreassen, J. Billieux, M. D. Griffiths et al., “The relationship between addictive use of social media and video games and symptoms of psychiatric disorders: a large-scale cross-sectional study,” *Psychology of Addictive Behaviors*, vol. 30, no. 2, pp. 252–262, 2016.
- [120] C. S. Andreassen, M. D. Griffiths, J. Hetland, and S. Pallesen, “Development of a work addiction scale,” *Scandinavian Journal of Psychology*, vol. 53, no. 3, pp. 265–272, 2012.
- [121] J. F. Helliwell and R. D. Putnam, “The social context of well-being,” *Philosophical Transactions of the Royal Society of London Series B: Biological Sciences*, vol. 359, no. 1449, pp. 1435–1446, 2004.
- [122] C. Kroll, *Social Capital and the Happiness of Nations. The Importance of Trust and Networks for Life Satisfaction in a Cross-National Perspective*, Lang, Frankfurt, 2008.
- [123] J. Han, X. Chu, H. Song, and Y. Li, “Social capital, socioeconomic status and self-efficacy,” *Applied Economics and Finance*, vol. 2, no. 1, pp. 1–10, 2015.
- [124] H. Dan, “Online social capital and psychological well-being among Chinese women during the COVID-19 pandemic: a cross sectional study,” *Higher Education and Oriental Studies*, vol. 1, no. 2, 2021.
- [125] C. Gilleard and P. Higgs, “Internet use and the digital divide in the English longitudinal study of ageing,” *European Journal of Ageing*, vol. 5, no. 3, pp. 233–239, 2008.
- [126] J. Palfrey and U. Gasser, *Born Digital: Understanding the First Generation of Digital Natives*, Perseus, New York, NY, 2008.
- [127] C. Serrano-Cinca, J. F. Muñoz-Soro, and I. Brusca, “A multivariate study of internet use and the digital divide,” *Social Science Quarterly*, vol. 99, no. 4, pp. 1409–1425, 2018.
- [128] B. Alzougool, “The impact of motives for Facebook use on Facebook addiction among ordinary users in Jordan,” *International Journal of Social Psychiatry*, vol. 64, no. 6, pp. 528–535, 2018.
- [129] S. L. Dailey, K. Howard, S. M. Roming, N. Ceballos, and T. Grimes, “A biopsychosocial approach to understanding social media addiction,” *Human Behavior and Emerging Technologies*, vol. 2, no. 2, pp. 158–167, 2020.
- [130] K. Kircaburun, S. Alhabash, Ş. B. Tosuntaş, and M. D. Griffiths, “Uses and gratifications of problematic social media use among university students: a simultaneous examination of the big five of personality traits, social media platforms, and social media use motives,” *International Journal of Mental Health and Addiction*, vol. 18, no. 3, pp. 525–547, 2020.
- [131] I. Süral, M. D. Griffiths, K. Kircaburun, and E. Emirtekin, “Trait emotional intelligence and problematic social media use among adults: the mediating role of social media use motives,” *International Journal of Mental Health and Addiction*, vol. 17, no. 2, pp. 336–345, 2019.