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The Social Media Use Scale: Development and Validation

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Abstract

Social media (SM) use has been primarily operationalized as frequency of use or as passive versus active use. We hypothesize that these constructs have shown mixed associations with psychological constructs because the factor structure underlying social media use (SMU) has not been fully identified. We conducted three studies with college students. In Study 1 (N = 176), we collected data about participants' SMU, informing item generation. In Study 2 (N = 311), we tested two factor structures: (a) passive, active social, and active non-social and (b) a hypothesized four-factor structure. Neither confirmatory model produced acceptable fits, but an exploratory factor analysis suggested a four-factor model: belief-based, consumption-based, image-based, and comparison-based SMU. This four-factor structure was supported in Study 3 (N = 397), which was preregistered, via a confirmatory factor analysis. The subscale items showed good internal consistencies, and evidence is presented for convergent validity. These factors represent a novel classification of people's SMU that can be measured with the Social Media Use Scale.

Keywords
social media, social networking sites, measure, passive and active, well-being

Use of social media (SM) has grown considerably over the past decade. Approximately 72% of adults in the United States report using SM, with the vast majority reporting that they use it daily (Pew Research Center, 2021). Among adults, the group who uses SM most frequently is college-aged adults: a striking 94% report using SM (Smith & Anderson, 2018). Despite these significant statistics, there is not an empirically validated measure that assesses how individuals use SM across a host of SM platforms. The current investigation aimed to develop such a measure.

First, it is important to describe how we define SM. We use the commonly adopted term, SM, to refer to social networking sites—online platforms that allow individuals to create profiles, connect with other users, and view their list of connections with others (e.g., Twitter, Facebook; Boyd & Ellison, 2007). Although SM technically refers to any platform in which users create and share content (e.g., YouTube, recipe websites; Boyd & Ellison, 2007), it has become increasingly common to use the term *social media* to refer to social networking sites. Supporting this, a review by Aichner et al. (2021) found that "social networking sites" was the term used more frequently before 2010, whereas "social media" has become the dominant term since 2010. Furthermore, we do not consider direct messaging in our definition of social media use (SMU), although direct messaging is a component of many SM platforms, because it is not unique to SMU.

Given the widespread use and growth of new users of SM along with findings that rates of mental illness have increased over recent years (Richter et al., 2019), researchers have been quick to begin examining associations between how people use SM and their psychological well-being. There is a large literature examining how SMU relates to various forms of psychological functioning, including depression, anxiety, loneliness, happiness, and psychological well-being. However, much of this research has yielded inconsistent findings. For instance, researchers have highlighted the largely mixed findings regarding associations between SMU and constructs such as self-esteem (Saiphoo et al., 2020), depression and anxiety (Seabrook et al., 2016), and general psychological well-being (Erfani & Abedin, 2018). These

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inconclusive findings are troubling since SM is here to stay, likely as a permanent fixture in modern society. Understanding how the ways in which people engage with SM are associated with psychological well-being is critical. Clarifying these associations is a crucial step to understanding how people could modify their use to engage in healthier SMU, thereby promoting psychological well-being.

We posit that these equivocal findings are a result of there not being a consensus about which aspect(s) of SMU should be assessed. Researchers have primarily focused on two different aspects of how individuals use SM. The first is simply time per day spent on SM, and this body of work has perpetuated inconclusive findings with regard to predicting psychological outcomes. For instance, some have found that more time per day spent on SM is associated with higher levels of depressive symptoms, whereas others have found negative or null associations (Huang, 2017; Seabrook et al., 2016). Similarly, mixed findings have been found when examining associations between time per day spent on SM and psychological well-being (Verduyn et al., 2017). Indeed, Coyne et al. (2020) underscored a need for researchers to move beyond a focus on time per day on SM after their 8-year longitudinal study found no associations between SM screen time and symptoms of depression or anxiety.

The second major focus of assessing how people engage in SMU has been on examining "passive" versus "active" use. Conventionally, passive SMU is defined, broadly, as non-directed consumption of SM content (sometimes referred to as "lurking"; Escobar-Viera et al., 2018). Active SMU, although also broadly defined, is understood as directed engagement in social connections on SM (sometimes referred to as "directed communication"; Burke et al., 2010). Research has often found that active use is associated with greater psychological well-being, whereas passive use is associated with worse psychological well-being (Escobar-Viera et al., 2018; Wang et al., 2018), potentially because passive SMU can facilitate social comparison and impression management (e.g., Zhu & Bao, 2018). However, several investigations contradict these findings; active SMU has also been found to be negatively associated with psychological well-being (e.g., Shensa et al., 2018), and analyses of passive versus active use have resulted in null associations as well (Tartaglia & Bergagna, 2022). Others have found ambiguous results. Beyens et al. (2021) created a SMU scale differentiating SMU into active private, passive private, and passive public SMU in adolescents, although it is important to note the authors did not examine the scale's factor structure. They found that the effects of these different types of SMU showed individual differences, concluding that "the active–passive use dichotomy in social media research is less clear-cut than it might seem" (Beyens et al., 2021, Abstract section). Indeed, a review by Valkenburg, van Driel, and Beyens (2022) found that associations between passive versus active use and psychological well-being (e.g., life satisfaction; depressive symptomology) have been largely inconsistent, highlighting the mixed findings in the literature. It is for reasons such as this that researchers have argued that more fine-grained measures of SMU should be developed to further examine the long-term effects of different types of SMU (Boer et al., 2022; Jensen et al., 2019).

There is only one measure empirically developed to assess types of SMU, which expands some upon the passive-active conceptualization: The Passive and Active Facebook Use Measure (PAUM; Gerson et al., 2017). The PAUM is a 13-item scale that differentiates Facebook use into three categories: active-social (e.g., "posting status updates"), active non-social (e.g., "tagging videos"), and passive (e.g., "viewing photos"). The PAUM expands conceptualization of active SMU by differentiating between activities related to directly communicating with others (i.e., active social) versus creating content (i.e., active non-social). Despite its strong psychometric properties, the PAUM is not without limitations like all measures. It does not differentiate between activities related to passive SMU. That is, the PAUM does not consider the differences between passive SMU aimed at consuming content versus passive SMU aimed at evaluating others and oneself, which is a critical limitation given social comparison and impression management are known to take place on SM (e.g., Zhu & Bao, 2018). In addition, the PAUM was developed for use on Facebook only and includes activities specific to that platform's structure in 2017. It is likely for this reason that the PAUM is not commonly used to evaluate engagement in types of SMU.

More broadly, there are notable limitations in measuring SMU in terms of passive and active categories. First, researchers often create their own non-validated scales assessing engagement in passive versus active activities, possibly because the only scale empirically developed to examine SMU is for Facebook. These passive-active constructs are ambiguously defined, and indeed, a review of the effects of passive and active SMU on psychological well-being found that 90% of the articles reviewed used a unique definition of passive and active SMU with 29 variations of response scales (Valkenburg, van Driel, & Beyens, 2022). Trifiro and Gerson (2019) have urged researchers to develop a new, universal measure for assessing passive and active SMU—one that can be used across a host of SM platforms and is less susceptible to the ever-evolving nature of these sites. Until such a measure is developed, researchers will continue to use different and non-validated measures, and this non-standardized approach means that mixed and inconclusive findings in the literature will persist.

An additional crucial consideration regarding assessing SMU in terms of passive and active use is that these constructs may simply not be an adequate representation of the range of ways in which individuals use SM. Activities engaged in on SM are nuanced and may not be able to be coerced into strictly passive versus active—or social versus non-social—categories. For reasons such as this, researchers have recommended that more nuanced measures of SMU be developed (Kross et al., 2021; Saiphoo et al., 2020). In addition, SM has rapidly evolved over the past several years and may now be used in a host of different ways. It is important that researchers examine SMU from a macro perspective and consider whether there may be better ways of conceptualizing the ways in which individuals use SM.

It is critical that a well-validated and more nuanced SMU scale be developed for several reasons. First, there is evidence that self-report measures correlate with objective measures, at least in ecological momentary assessment (EMA) contexts (Verbeij et al., 2021, 2022). In addition, self-report measures of SMU are more practical and often more cost effective than collecting objective SM usage. Furthermore, self-report measures allow for nuances that objective indicators of SMU simply cannot provide. For instance, while researchers may be able to record how long someone spends on SMU each day by tracking app usage on participants' phones, researchers cannot know how these sites are being used (e.g., to engage in social comparison), which is likely to influence psychological well-being. The most effective and efficient way to understand how individuals engage in different types of SMU is to ask them. Researchers need a scale that is developed and validated to assess SMU across a host of different platforms to collect data in valid and reliable ways.

In the current investigation, we aimed to develop and provide convergent validity for a new, global SMU questionnaire by focusing on the wide range of activities in which individuals engage on these platforms. We thought that the general structure of active social, active non-social, and passive use was a strong conceptualization that required more nuance and expansion. We hypothesized that SMU would be best captured by an expanded four factors composed of SM activities that are similar, in essence, to the active social, active non-social, and passive conceptualization. We preliminarily called these factors active voicing, active content seeking, passive browsing, and passive image managing.

Importantly, although the literature has not considered age when measuring the factor structure of different types of SMU, we suspected that this conceptualization would generalize across the lifespan. For instance, older adults may spend more time looking at pictures of their grandchildren, whereas younger adults may spend more time looking at pictures of their close friends, but both activities would reflect similar passive consumption purposes. In the current study, we utilized a young adult sample because they represent the largest adult population of SM users (Pew Research Center, 2021). However, we acknowledge that this means that future research is needed to examine the factor structure of SMU among different age groups of SM users.

We hypothesized that active voicing would be a category of SMU that included activities such as posting, commenting, and generally sharing one's voice on SM. Active voicing was expected to describe all forms of SMU related to creating content and communicating with others, thereby capturing the essence of active social use. We thought that active content seeking on SM would consist of activities related to actively seeking information and content to consume on SM. Active content seeking was expected to describe forms of SMU related to actively engaging in these platforms without an explicitly social motive, thereby capturing the essence of active non-social use. We hypothesized that passive browsing and passive image managing were factors that would expand upon the conventional broader conceptualization of passive SMU. We predicted passive browsing would be a category of SMU consisting of activities related to a passive and non-goal directed consumption of SM content. Passive browsing was expected to describe forms of SMU related to passively consuming content, thereby capturing the passive entertainment essence of passive SMU. Passive image managing was hypothesized to capture experiences related to social comparison and impression management, specifically. Passive image managing was expected to describe forms of SMU related to social monitoring, which is often thought to explain why passive SMU may predict negative well-being outcomes, as described above. However, this construct has not been incorporated into the measurement of passive SMU to date.

To examine convergent validity, we additionally assessed several constructs related to beliefs, behaviors, and personality that were consistent with our conceptualizations of the four factors. We expected that specific traits would have unique associations with specific subscales, thereby demonstrating that behaviors on SM correlate with similar trait-like tendencies. We predicted that active voicing would be most positively uniquely associated with traits related to a drive to be publicly vocal, including extraversion, narcissism, and need for drama. Active content seeking was hypothesized to be most positively uniquely associated with boredom susceptibility. Passive browsing, we predicted, would be most positively uniquely associated with enjoyment on SM and emotion regulation goals characterized by attempts to upregulate positive affect and downregulate negative affect. We hypothesized that passive image managing would be uniquely associated with many clinically relevant constructs, including increased depression, social physique anxiety, fear of negative evaluation, and need for approval, and decreased self-esteem. Of note, we thought that these trait measures were important to consider regardless of whether our four-factor structure was supported since these traits are likely to be implicated in SMU in a variety of different ways.

The current investigation consisted of three studies. For each study, we recruited a large and different sample of undergraduate students. In Study 1, we first developed our scale using qualitative methods. In Study 2, we tested our central hypotheses about the factor structure of SM. The first model we tested consisted of our hypothesized four-factor structure (Model 1). We also tested a factor structure consistent with the active social, active non-social, and passive use conceptualization (Model 2). We additionally conducted an exploratory factor analysis to determine the factor structure with optimal model fit (Model 3). We further investigated how the final factors from the best-fit model were associated with various trait measures to examine their convergent validity. For Study 3, which we preregistered, we conducted two confirmatory factor analyses based on results from Study 2. We also aimed to replicate associations between SMU factors and trait measures and administered new measures to show additional support for convergent validity. We report how we determined our sample size, all data exclusions, all manipulations, and all measures in the study.

Study 1

Background

The goal of Study 1 was to establish a comprehensive list of activities that individuals report doing on SM. We sought to capture activities that were objective (i.e., "read, watched, or caught up on news"), relatively subjective (e.g., "actively sought out content that I morally or ethically disagreed with"), and emotional (e.g., "read or watched news with content that I found negative or upsetting"). Throughout this process, we aimed to describe SM activities in a flexible way such that they could be related to a variety of SM platforms, not a specific one. And although we do not know precisely how SMU will change in the years to come, we tried to describe items such that they could be flexible even as these platforms evolve. For example, we included the item, "Posted or sent a picture(s) about positive events or emotions" because "posting" or "sending" pictures has been a stable and ubiquitous component of all SM platforms. We took a twofold approach to develop the initial list of SM activities that included creating a list ourselves and then collecting open-ended responses from participants in a target group. As such, we were able to capture the constructs that we thought were critical to understanding SM activities (i.e., ones that were objective, subjective, and emotional) and cross-reference these constructs with the SM activities participants in the target group reported.

Methods

Participants. Sample 1 consisted of 176 students (54% women) recruited from a participant pool at a private university in the Midwestern United States. Participant ages ranged from 18 to 23 years (M = 20.00, SD = 1.26). Regarding race and ethnicity, participants identified as follows: 45% White, 27% Asian, 20% Black, 9% multiracial, 10% Hispanic or Latinx.

Students learned about the study via a portal that lists active studies. The entire study was administered online, and participants were compensated with course research credit. Procedures were approved by the university's Human Research Protection Office.

Procedures. Participants first indicated consent to participate by clicking that they agreed on the consent document, which was the first page of the online study. Then they were provided with information on what they would be instructed to do in the study. Namely, participants would use their own SM for 3 minutes on any device of their choosing. They were told they could use Facebook, Instagram, Twitter, Snapchat, Reddit, Tumblr, and/or LinkedIn. They could use more than one site if desired. These SM platforms were selected based on two selection criteria: (a) SM on which some of the people in one's online network are people whom one is likely to know "in real life" and/or (b) there is a significant focus on both consuming *and* commenting on content, since it is imperative to include sites on which a wide range of activities can be captured. In addition, platforms that are strictly text/communication based (e.g., Facebook Messenger) were excluded because direct texting communication is not unique to SM and was outside the scope of the current study. Participants were told not to engage in direct messaging during the study (e.g., Snapchat direct messaging).

Participants were prompted when to begin using their SM, and a chime rang at the end of 3 minutes to direct them back to the survey. Participants were then presented with a text box in which they were asked to write everything they could remember doing on SM during the previous 3 minutes and which SM platform(s) they used. After providing the qualitative description, participants completed a series of self-report measures, which are not related to the current study.

SMU Activities. We developed an initial list of SM activities by creating experimenter-generated items. We consulted with several undergraduate research assistants and their peers to gain information about what they do on SM. This initial endeavor yielded a list of 45 discrete SM activities (see Table S1 in supplementary materials).

The first author of this article and a trained undergraduate research assistant independently read and coded each of the participants' open-ended reported activities to assess whether (a) each activity individuals reported could be captured by the developed list and (b) wording of activities on the list adequately reflected wording individuals use to describe these activities. Responses were coded as the SM activities from the developed measure, and inter-rater agreement was calculated using Cohen's Kappa. Inter-rater reliability was determined to be high (κ = .91).

Results and Discussion

In Study 1, participants engaged in SMU using their own mobile devices or computer for 3 minutes. After doing so, in their own words, participants described the SMU activities they engaged in and which SM platforms they used. The number of SM platforms in which participants reported engaging ranged from 1 to 3 (M = 1.31; SD = 0.56). Regarding specific SM platforms, usage was reported as follows: 59.06% Instagram, 25.73% Snapchat, 19.88% Twitter, 12.86% Facebook, 12.28% Reddit, .01% Tumblr, and .01% LinkedIn.

We had put together an initial item pool of 45 SMU activities that we thought represented a comprehensive list. We used this list to code participants' free response descriptions of SMU activities. Based on results from the coding process, we made five changes to the initial item pool of 45 SM activities. First, we removed mention of any emotional impact of activities from items because most participants reported on activities without noting such. Furthermore, we thought that some activities on SM likely produce mixed emotional responses, and therefore ascribing a specific emotion is challenging (consolidating 21 items to nine items). For example, the three items "Read or watched news with content that I found negative or upsetting (Item 1o)," ". . . neutral (neither positive nor negative)" (Item 1p), and ". . . positive or happy" (Item 1q) were consolidated into one item: "Read, watched, or caught up on news or current events (Item 2l). Second, we modified the language of 16 activities to more closely match how individuals described them (including consolidating nine items to four items). For example, we merged items about "making" and "sharing" posts into combined items about making/sharing posts, since several participants appeared to use these terms interchangeably. Third, we determined that it was important to differentiate between personally relevant and non-personally relevant sharing of information on SM, so we expanded items that reflected making SM posts (expanding two items to four items). For example, we included the two items "Made/shared a post or story about something negative that was NOT personally about me" (Item 2a) and "Made/shared a post or story about something negative that was personally about me" (Item 2b). Fourth, we removed one item that was never endorsed ("played a game"). Finally, we added two new activities that had not been included in the initial item pool (e.g., "Made/shared a post or story about fundraising or benefits"). The updated measure included a total of 31 SM activities. See Table S1 in supplementary materials for specific changes made to items after Study 1.

The open-ended response format was an important design element to Study 1 because it allowed participants to report on their SMU activities without being confined to reporting on predefined categories of SMU such as "passive" and "active" activities. This is the first study to create a SM scale based on open-ended data collection methods. A caveat to this study design was that since participants could only engage in SMU for 3 minutes, it is possible that we did not capture every type of SMU activity. However, this design element made it likely that participants remembered what they did over the 3-minute time period versus a longer one. It was reassuring that all but one activity initially included in our 45-item pool was reported by participants, suggesting people were in fact engaging in a wide range of SMU activities. In fact, participants engaged in two additional activities during this short timeframe.

Study 2

Background

With the list of SM activities determined by Study 1, we had three primary aims for Study 2. First, we sought to determine the factor structure of items in the SM scale. Second, based on the scale's factor structure and item loadings, we aimed to determine which items from our 31-item scale should be retained in or removed from the final measure. Finally, we aimed to find evidence for convergent validity of our scale.

Methods

Participants. A total of 311 participants (64% women, 34% male, .29% nonbinary) were recruited from a

Table 1. Primary Factor Item Loadings for the Confirmatory Factor Analyses in Samples 2 and 3.

	Image		Compare		Belief		Consume	
Item	S2	S3	S2	S3	S2	S3	S2	S3
Looked at how many people liked, commented on, shared my content, or followed/friended me	.77	.82						
Edited and/or deleted my own social media content	.76	.66						
Played with photo filtering/photo editing	.75	.65						
Made/shared a post or story about something positive that was personally about me	.73	.65						
Read comments to my own content	.69	.74						
Compared my life or experiences with others'			.81	.82				
Compared my body or appearance with others'			.71	.75				
Reminisced about the past			.61	.61				
Made/shared a post or story about something negative that was NOT personally about me					.85	.80		
Made/shared a post or story about something negative that was personally about me					.68	.71		
Commented unsupportively or disliked/"reacted" unsupportively on other's post(s)					.65	.55		
Sought out content that I morally or ethically disagreed with					.57	.57		
Navigated to others' profiles in my social network (e.g., friends or friends of friends)							.79	.78
Looked at others' stories							.75	.70
Navigated to others' pages who I do not know (e.g., influencers or other famous people)							.67	.71
Scrolled aimlessly through my feed(s)							.64	.60
Watched videos such as memes, news content, and how-tos/recipes.							.45	.52

Note. Items in each factor are listed in descending order based on Study 2 loading size. Image = image-based; Compare = comparison-based; Belief = belief-based; Consume = consumption-based; S2 = Study 2; S3 = Study 3.

participant pool at a private university in the Midwestern United States. DeVellis (2016) recommends that scale development researchers recruit a minimum sample of 300 participants, a sufficiently large sample to minimize subject variance as a significant concern. Individuals who had participated in Study 1 were ineligible to participate in Study 2. Participant ages ranged from 18 to 23 years (M = 19.24, SD = 1.15). About 10% identified as Hispanic, Latino(a), or Latinx. Regarding race, our participants in this sample identified as follows: 55% White, 28% Asian, 10% African American or Black, 7% multiracial, 0.01% American Indian or Alaska Native. Participant recruitment and compensation was identical to Study 1.

Procedures. The study was administered online. After reading and agreeing to the informed consent, participants were presented with our SMU scale. Participants additionally completed 12 questionnaires to assess various traits of interest, the order of which was randomized across participants. Internal consistencies for items were calculated for each trait measure administered. These alpha values can be found in Table 2.

Measures

SMU. Participants were first presented with our list of 31 SM activities. The order of these activities was randomized for each participant. For each activity, participants were asked to rate how frequently they had engaged in the activity on platforms including Facebook, Instagram, Twitter, Snapchat, Reddit, Tumblr, and LinkedIn over the previous 7 days on a 9-point Likert-type scale from 1 (*never*) to 9 (*hourly or more*). This scale was chosen because 9-point response scales often outperform other rating scales (e.g., 5-point response scales) with regard to reliability and validity (Preston & Colman, 2000). Furthermore, using more (versus fewer) Likert-type scale points is shown to result in a more normal distribution of the data, allowing researchers to better treat the data as interval (versus ordinal), which is consistent with the theory of our response scale (H. Wu & Leung, 2017). Specific scale point anchors were developed in consultation with undergraduate students and with the aim of constructing a scale theoretically close to interval, in which points have an order and the difference between two points is roughly equal. Like in Study 1, participants were instructed not to report on activities related to direct messaging.

Table 2. Cronbach's Alphas and Standardized Betas for Each Multiple Regression Model of the Factors Predicting Each Trait Variable in Samples 2 and 3.

	α		Image-based		Comparison-based		Belief-based		Consumption-based	
Variable	S2	S3	S2	S3	S2	S3	S2	S3	S2	S3
SM enjoyment	.82	.82	.14*	.11	–.01	–.06	–.06	–.08	.31*	.25*
Frequency of SMU	—	—	—	.04	—	–.07	—	.20*	—	.47*
Average time on SM	—	—	—	.24*	—	–.03	—	–.08	—	.23*
Self-promotion impression management	—	.86	—	.24*	—	–.05	—	–.04	—	.02
Exhibitionism narcissism	.84	.83	.21*	.16*	.03	.09	–.01	–.04	.12	–.01
Social anxiety	—	.92	—	–.03	—	.24*	—	.11	—	–.02
Social domain security	—	.93	—	.08	—	–.27*	—	–.11	—	.08
Boredom susceptibility	.49	.47	.03	–.01	–.05	.01	.24*	.22*	–.02	.01
Need for drama	.83	.82	.05	.15*	.11	.06	.30*	.18*	–.05	–.01
Self-esteem	.89	.87	.10	.08	–.37*	–.28*	–.14*	–.17*	.17*	.00
Depression	.91	.91	–.07	.02	.41*	.29*	.18*	.19*	–.16*	–.05
Pro-hedonic ER goals	.76	.79	.19*	.11	.12	.06	–.19*	–.11	.03	.07
Contra-hedonic ER goals	.85	.82	.03	.08	.22*	.15*	.24*	.26*	–.23*	–.05
Pro-social ER goals	.84	.83	.04	.11	.21*	.22*	.00	–.14*	.08	.02
Impression management ER goals	.87	.85	.07	.02	.27*	.32*	.01	–.03	.02	–.03
Fear of negative evaluation	.91	.90	–.12	–.08	.45*	.40*	–.04	–.07	.00	–.02
Social physique anxiety	.90	.90	–.10	.02	.43*	.37*	–.07	–.04	.03	–.10
Need for approval	.76	.77	.03	.02	.21*	.17*	–.01	–.11	–.02	.02
Negative emotionality	.90	.89	–.13	.02	.39*	.31*	.02	–.17*	–.06	–.06
Openness	.83	.87	.02	–.01	.15	.17*	–.12	–.14*	–.09	–.11
Conscientiousness	.85	.82	.09	.01	–.09	.09	–.18*	–.14*	–.02	–.05
Extraversion	.89	.87	.15*	.13	–.13	–.01	–.04	–.10	.16*	.03
Agreeableness	.81	.81	.03	.04	.08	.01	–.30*	–.19*	.02	.04
Life satisfaction	—	.86	—	.09	—	–.12	—	–.12*	—	.07

Note. S2 = Study 2; S3 = Study 3; SM = social media; SMU = social media use; ER = emotion regulation.
*$p < .05$.

SM Enjoyment. We assessed the extent to which individuals enjoy using SM with a 5-item scale adapted from Turel and Serenko (2012). Items were adapted such that each referred to social networking sites more generally as opposed to a single, preferred SM platform (e.g., "Using this social networking site is pleasurable" became "Using social networking sites is pleasurable"). Each item is scored from 1 (*strongly disagree*) to 5 (*strongly agree*), and items have demonstrated excellent internal consistency in a student sample ($\alpha = .95$; Turel & Serenko, 2012). Internal consistency in the current sample was good.

Personality. We measured extraversion, open-mindedness, conscientiousness, agreeableness, and negative emotionality by administering the Big Five Inventory 2 (BFI-2; Soto & John, 2017). This scale consists of 60 characteristics for which participants rate to what extent the characteristic applies to them from 1 (*disagree strongly*) to 5 (*agree strongly*). Sample characteristics include "is talkative" (extraversion), "is curious about many different things" (open-mindedness), "is dependable, steady" (conscientiousness), "is compassionate, has a soft heart" (agreeableness), and "can be tense" (negative emotionality). This scale has been developed and tested in undergraduate students, and the subscales correlate well with longer measures (α for student sample = .80–.88; Soto & John, 2017). Internal consistencies of items for subscales in the current sample were good to excellent.

Fear of Negative Evaluation. We measured fear of negative evaluation with the Brief Fear of Negative Evaluation Scale (Leary, 1983). This scale consists of 12 items scored from 1 (*not at all characteristic of me*) to 5 (*extremely characteristic of me*). A sample item includes "I am usually worried about what kind of impression I make." It has demonstrated good internal consistency of items ($\alpha = .80$) and has been shown to correlate highly with similar measures (Duke et al., 2006). Internal consistency of items in the current sample was excellent.

Self-Esteem. We measured self-esteem using the Rosenberg Self-Esteem Scale (RSE; Rosenberg, 1979). This scale contains 10 items scored from 1 (*strongly agree*) to 4 (*strongly disagree*), with a sample item including “I feel that I have a number of good qualities.” Internal consistency for the RSE has ranged from .77 to .88 (Rosenberg, 1979). Internal consistency of items in the current student sample was good.

Depression. We assessed depression with the 20-item Center for Epidemiological Studies-Depression scale (CES-D; Radloff, 1977). The CES-D is scored with regard to the past week from 0 (*never or none of the time (less than 1 day)*) to 3 (*most or all of the time (5 to 7 days)*) and was designed for use in non-clinical samples. A sample item includes “I felt sad.” Internal consistency of items in the current student sample was excellent.

Social Physique Anxiety. We measured participants' anxiety concerning perceptions of their appearance using the Social Physique Anxiety Scale (SPAS; Hart et al., 1989). The SPAS is a 12-item scale ranging from 1 (*not at all characteristic of me*) to 5 (*extremely characteristic of me*). A sample item includes “In the presence of others, I feel apprehensive about my physique or figure.” The SPAS was developed with a college student sample (α = .90; Hart et al., 1989), and internal consistency of the items in the current sample was excellent.

Need for Approval. We assessed need for approval, or individuals' concern with their public image, with the Martin-Larsen Approval Motivation Scale (MLAMS; Martin, 1984). The MLAMS is a 20-item scale scored from 1 (*disagree strongly*) to 5 (*agree strongly*) and has been examined in undergraduate samples (Leary et al., 2015). A sample item includes “I change my opinion (or the way that I do things) in order to please someone else.” Internal consistency of items in the current sample was good.

Need for Drama. We measured participants' propensity to incite and manipulate others by assessing their need for drama (Frankowski et al., 2016). The Need for Drama (NFD) measure is a 12-item scale scored from 1 (*not at all characteristic of me*) to 5 (*extremely characteristic of me*). A sample item includes “sometimes it's fun to get people riled up.” Items in the NFD have demonstrated good internal consistency (α = .77–.86; Frankowski et al., 2016), and internal consistency in the current sample was good.

Boredom Susceptibility. We assessed individuals' aversion to experiencing boredom with the boredom susceptibility subscale of the Zuckerman Sensation Seeking Scale-V (Zuckerman, 2007). This subscale consists of 10 items each containing a pair of related, but distinct scenarios. A sample pair includes “The worst social sin is to be rude; The worst social sin is to be a bore.” For each pair, participants indicate which of the two scenarios they would prefer. Although items in the boredom susceptibility subscale of the Zuckerman Sensation Seeking Scale-V have demonstrated good internal consistency in some samples (α = .74; Zuckerman, 2007), internal consistency of items in the current sample was poor. Indeed, this appears to be a trend in the literature, and a review of studies utilizing the Zuckerman Sensation Seeking Scale-V found overall low reliability for the boredom subscale (Deditius-Island & Caruso, 2002).

Exhibitionism Narcissism. We measured exhibitionism narcissism—defined as a desire to be noticed, popular, or the focus of the attention—with the exhibitionism narcissism subscale of the Five Factor Narcissism Inventory (FFNI; Glover et al., 2012; Miller et al., 2013). This subscale contains 10 items scored from 1 (*disagree strongly*) to 5 (*agree strongly*). A sample item includes “I like being noticed by others.” The FFNI was developed with a college student sample (Glover et al., 2012), and internal consistency of items in the current sample was good.

Emotion Regulation Goals. We assessed reasons for regulating emotions with the Emotion Regulation Goals Scale (ERGS; Eldesouky & English, 2019). The ERGS consists of 18 items scored from 1 (*never*) to 7 (*always*). It contains five subscales which assess the extent to which individuals regulate their emotions: pro-hedonic goals, contra-hedonic goals, performance goals, prosocial goals, and image-based goals. Example emotion regulation goals/items include, “to feel more positive emotion (e.g., joy, contentment)” (pro-hedonic goals), “to feel more negative emotion (e.g., anger, sadness)” (contra-hedonic), “to maintain a close relationship with others” (pro-social goals), and “to make a positive impression on others” (image-based). For the purposes of this study, we did not assess performance-related emotion regulation goals. Subscale items of the ERGS have demonstrated good internal consistencies in a college student sample (α = .74–.85; Eldesouky & English, 2019). Internal consistencies for subscale items in the current sample were good.

Analytic Plan. To test our hypothesized factor structure against the commonly accepted structure discussed in the literature, we first conducted a confirmatory factor analysis for each. To ensure optimum model fit, we additionally conducted an exploratory factor analysis. All analyses were conducted in R Data Analysis Software (R Core Team, 2022). Items were treated continuously and with maximum likelihood with robust standard errors (MLR) estimation, an estimation method where the data are assumed to follow a multivariate normal distribution and where standard errors are *robustly* and more accurately estimated (Maydeu-Olivares, 2017). None of the participants in the current sample had missing SMU activity data, so all analyses were conducted with complete observations.

We began by conducting confirmatory factor analyses for each of the two models being tested. Model 1 was our hypothesized four-factor model (active voicing, active content seeking, passive browsing, and passive image managing). Model 2 was a three-factor model composed of active social, active non-social, and passive SMU. See Table S2 in supplementary materials for hypothesized activity loadings for each model. With regard to establishing adequate factor fit, we considered the following fit indices: the comparative fit index (CFI; Hu & Bentler, 1999), the root mean square error of approximation (RMSEA; Hu & Bentler, 1999), and the standardized root mean square residual (SRMR; Schumacker, 1992). We aim to derive models with a CFI $> .90$, an RMSEA $< .06$, and an SRMR $< .08$ (Hu & Bentler, 1999; Schumacker, 1992).

To ensure optimal model fit, we additionally conducted an exploratory factor analysis. We did so by first conducting a parallel analysis to determine the number of latent variables possibly underlying the data (Floyd & Widaman, 1995). Since we sought to achieve simple structure, such that each item loaded highly on as few factors as possible, we utilized oblimin rotation in the exploratory factor analysis (Floyd & Widaman, 1995).

After the optimal factor structure was determined, we examined item loadings to determine which items to retain in the measure. A common rule of thumb in the literature for establishing cutoff criteria is the .40–.30–.20 rule: That satisfactory items load onto their primary factor at .40 or above, load onto alternative factors below .30, and have a difference of .20 between their primary factor and any alternative factors (Howard, 2016). These rules were employed to help determine which items were candidates for retention in the 31-item questionnaire. In addition, we considered the number of items included in each factor. That is, it is considered best practice that a scale consist of subscales that each have a similar number of items (DeVellis, 2016). Consequently, we made initial determinations to remove and retain items based on both the .40–.30–.20 rule and in efforts to ensure the most similar number of items across factors as possible. If it was ambiguous whether we should keep an item based on these two rules, we considered the factor structure of the scale with versus without that item and selected the scale version with best model fit. Once decisions regarding item removal and retention were made, we conducted a confirmatory factor analysis on these items to ensure good model fit.

For our finalized model, we computed (a) internal consistencies for each factor and (b) correlations between factors to ensure that (a) item responding for each factor was reliable in the current data and (b) the factors were distinct from one another. Item responding was deemed reliable if Cronbach's alpha was greater than .70 (Taber, 2018). Factors were determined to be distinct if their correlations with one another were less than .70 (Costello & Osborne, 2005).

We ended by conducting multiple regression analyses in which the standardized score on each of the assessed trait measures was predicted by standardized scores for all factors in the final model. Since our factor analyses utilized oblique rotation, allowing factors to correlate, it was likely that more than one factor would significantly correlate with the same trait. Consequently, we examined how each trait was associated with the factors controlling for all other factors. Resulting beta coefficients represented partial correlations between the trait measure and each factor.

Transparency and Openness. All raw data and analytic code for Study 2 have been made available through the Open Science Foundation (https://osf.io/6fxu4/).

Results

We first conducted confirmatory factor analyses for our two hypothesized models: Model 1, our primary hypothesized model (active voicing, active content seeking, passive browsing, and passive image managing), and Model 2, the conventionally understood model of SMU (active social, active non-social, and passive SMU). Fit indices for Model 1 did not meet established thresholds for adequate model fit (CFI = .79; RMSEA = .07; SRMR = .08). We next tested Model 2. Again, fit indices for these three factors did not meet established threshold values for adequate model fit (CFI = .77; RMSEA = .07; SRMR = .08).

We next conducted an exploratory factor analysis. First, we conducted a parallel analysis on the full data set. This analysis revealed that four factors may meaningfully underlay the data. Consequently, our exploratory factor analysis was conducted for a four-factor model utilizing oblimin rotation. Item loadings for each of the four factors can be found in Table S3 in supplementary materials. We used these item loadings to determine candidates for item removal and retention in the full scale. First, we employed the .40–.30–.20 rule (Howard, 2016). This initial effort yielded a total of 19 items as candidates for retention: five items in the first factor, three items in the second, four in the third, and seven in the fourth. We next made one decision and considered another to ensure the most similar number of

Table 3. Internal Consistencies for and Correlations Between Each of the Four Factors.

	α		1		2		3		4	
Factor	S2	S3	S2	S3	S2	S3	S2	S3		
1. Image-based	.86	.83	—	—						
2. Comparison-based	.75	.77	.46	.50	—	—				
3. Belief-based	.78	.76	.50	.55	.32	.29	—	—		
4. Consumption-based	.77	.80	.43	.39	.50	.52	.25	.20	—	—

Note. S2 = Study 2; S3 = Study 3.

items for each factor. First, we merged two out of three items with the smallest loadings from the fourth factor (i.e., "Looked at or watched memes" and "Looked at or watched videos such as how-tos/recipes, and DIY projects") into one item ("Watched videos such as memes, news content, how-tos/recipes, etc.") because they were quite similar in nature. We also dropped the other item with a small loading (i.e., "Read through my notifications"). This resulted in a total of five items for this subscale. Second, we considered including an additional item in the third factor (i.e., "Made/shared a post or story about something positive that was NOT personally about me"), which would result in a total of five items for this subscale as well. Adding this item in the scale would also allow the retention of parallel but distinct items (i.e., creating content that is versus is not of personal relevance) in the scale that we thought were important in understanding the differences between factors of SMU. Pending our decision to include versus exclude the aforementioned item in the third factor, our final scale consisted of 17 or 18 items. We conducted a confirmatory factor analysis on the full data set with just the 18 items (Model 3), and it demonstrated acceptable model fit (CFI = .91; RMSEA = .06; SRMR = .07). We then ran a confirmatory factor analysis with the 17-item version of the scale, which demonstrated slightly better fit (CFI = .92; RMSEA = .06; SRMR = .06). Consequently, all following analyses consider the 17-item version of the scale. Primary factor item loadings from the confirmatory factor analysis in Study 2 can be found in Table 1. We named the factors image-based, comparison-based, belief-based, and consumption-based SMU.

We next assessed internal consistencies for the items that composed each factor. Cronbach's alpha values were good (α = .75–.86; see Table 3). In addition, the four factors were significantly correlated, but not so strongly as to raise concerns about their distinctiveness. Factor correlations ranged from small (r = .25) to moderate (r = .50; see Table 3).

Finally, we conducted multiple regression models in which each trait was predicted by all four factors to examine convergent validity. See Table 2 for partial correlation coefficients between the four factors and trait variables. The unique associations between the four SMU factors and each trait measure are described in the discussion section below.

Discussion

The purpose of Study 2 was to determine the factor structure that best characterizes SMU. Findings did not support the four-factor structure (active voicing, active content seeking, passive browsing, and passive image managing) we hypothesized. Instead, we found support for a four-factor model consisting of categories related to image-based, comparison-based, belief-based, and consumption-based SMU. Items composing these factors demonstrated good internal consistencies, and the factors showed distinctiveness from one another. Consequently, we chose this as our final model composing the Social Media Use Scale (SMUS).

In Study 2, scores on each of the four factors correlated with administered trait measures in expected ways given the items that made up each factor. Consequently, findings provided support for convergent validity, despite the fact that we did not administer trait measures to provide evidence for convergent validity for these specific factors. Image-based SMU was uniquely positively associated with exhibitionism narcissism and a pro-hedonic emotion regulation tendency. That is, engaging in SMU to present a favorable social image or monitor the social image one may be making was associated with (a) having a desire to put oneself on display and (b) being motivated to upregulate one's positive emotions/downregulate negative emotions. These correlations are consistent with literature showing that focusing on one's own SM profile is associated with more positive self-views (Gentile et al., 2012) and fulfills users' need for self-worth and self-integrity (Toma & Hancock, 2013). Therefore, support for convergent validity was found for image-based SMU.

Comparison-based SMU, or using SM to compare oneself to others and/or to one's own past, was shown to be uniquely associated with numerous traits related to poorer psychological well-being (lower self-esteem, greater depression, fear of negative evaluation, social physique anxiety, need for approval, and negative emotionality). Interestingly, this type of use was also significantly positively associated with three out of the four emotion regulation goals assessed, including pro-social, impression management, and contra-hedonic, suggesting a desire to both perform well socially and upregulate negative emotions/downregulate positive emotions. Together, these findings suggest that comparison-based SMU is related to lower levels of social and emotional well-being as well as goals to regulate emotions for social and putatively maladaptive emotional reasons. These correlations would be expected based on the literature which has consistently found that social comparison is associated with negative psychological outcomes (e.g., Verduyn et al., 2020; Wirtz et al., 2021). This provides evidence for convergent validity for comparison-based SMU.

In Study 2, belief-based SMU, or using SM to feel or express negative opinions, was shown to be uniquely correlated with traits related to poorer psychological well-being (i.e., lower self-esteem, greater depression, and a contra-hedonic emotion regulation style). Belief-based SMU was associated with concurrent low levels of agreeableness and conscientiousness, which is notable because concurrent *high* levels of these two personality traits have been linked to greater happiness and psychological well-being (e.g., Soto, 2015). In addition, belief-based SMU was uniquely associated with increased boredom susceptibility and a propensity to engage in drama. Together, these findings suggest that engaging in belief-based SMU is associated with poorer emotional well-being and maladaptive social functioning. These correlations are consistent with literature suggesting that attending to negative news on SM is associated with higher levels of anxiety and poor self-control (Sharma et al., 2022) and lower levels of psychological well-being (Shabahang et al., 2022). Therefore, evidence for convergent validity was found for belief-based SMU.

In contrast to belief-based SMU, consumption-based SMU in Study 2 was uniquely associated with traits in ways suggesting greater emotional well-being (i.e., greater self-esteem and extraversion, and less depression and contra-hedonic emotion regulation goals). Furthermore, consumption-based SMU was uniquely associated with the greatest enjoyment on SM. It appears that using SM to simply consume seemingly entertaining content is associated with adaptive emotion regulation skills and greater psychological well-being, and it is possible that these adaptive traits are what lead to a tendency to enjoy SMU. These associations are consistent with literature showing that browsing-induced SMU enjoyment is associated with greater emotional well-being (Valkenburg, Beyens, et al., 2022) and that interest-driven exploration and browsing on SM can lead to being inspired and entertained (Weinstein, 2018). Therefore, evidence for convergent validity was established for consumption-based SMU.

Of course, it is imperative that the factor structure and its associations with trait measures be examined in additional samples. Replicating the SMUS's factor structure and its associations with various trait measures is the goal of Study 3 of the current investigation.

Study 3

Background

In Study 3, we aimed to test whether the four-factor structure of SMU found in Study 2 (i.e., image-based, comparison-based, belief-based, and consumption-based; Model 3) characterized SMU well in a new sample. We additionally aimed to replicate associations between each type of use and related traits. Because the factor structure found in Study 2 was not hypothesized, the traits we initially measured to provide evidence for convergent validity did not map perfectly onto the best supported factor structure. Consequently, we aimed to provide more targeted evidence for convergent validity in Study 3, especially for image-based, comparison-based, and consumption-based SMU.

We predicted the extent to which people engage in SMU would be associated with consumption-based SMU since those who engage in SMU for entertainment purposes likely spend more time on it. We included three trait measures related to people's concerns with public image, which we hypothesized would be positively associated with image-based SMU: Self-promotion impression management style, social anxiety, and social domain security. We also measured life satisfaction, which we thought would be positively associated with consumption-based SMU (i.e., the type of SMU that appears associated with the most positive outcomes) use and negatively associated with comparison-based SMU (i.e., the type of SMU that appears associated with the most negative outcomes). Hypotheses and all other study components of Study 3 were preregistered through the Open Science Foundation prior to data collection (https://osf.io/6fxu4/).

Methods

Participants. A total of 397 participants (53% women, 45% male, 2% nonbinary) were recruited from a participant pool at a private university in the Midwestern United States. Individuals who had participated in

Studies 1 or 2 were not eligible to participate. Recruitment strategies were identical to those used in the previous two studies. Participant ages in the current sample ranged from 18 to 22 years (M = 19.11, SD = 1.07). Reported racial and ethnic identities were as follows: 53% White, 27% Asian, 12% African American or Black, 7% multiracial, 0.002% American Indian or Alaska Native, and 12% Hispanic or Latinx.

Procedures. All general procedures were identical to Study 2. The study was administered online, and after agreeing to the informed consent, participants were presented with the 18-item version of the SMUS. We decided to administer the 18-item (versus 17-item) version to determine how the inclusion of the one additional item we considered in belief-based SMU ("Made/shared a post or story about something positive that was NOT personally about me") may have impacted model fit. Participants additionally completed the same series of 12 questionnaires plus five more to assess traits of interest. The order of these trait measures was randomized for each participant. Participants read a debriefing statement at the end of the study.

Measures. All measures from Study 2 were administered in Study 3. In addition, we administered those described below. As shown in Table 2, reliabilities for the items composing each scale ranged from good to excellent (α = .77–.93). The only exception was, again, our measure of boredom susceptibility, which demonstrated poor reliability. Internal consistencies for the trait measures administered in Study 3 can be found in Table 2.

SMU. Participants were first presented with the SMUS. We administered the 18-item version. All other components of the scale were identical to those in Study 2.

Extent of SMU. We assessed the extent to which individuals reported using SM by measuring frequency of SMU in the past week and average time per day spent on these sites. Individuals were asked how frequently, in the past week, they had used each of the seven sites on a Likert-type scale ranging from 1 (*never*) to 9 (*7 + times per day*). Next, participants reported in a text box about how many minutes in a typical day they use each of the seven SM sites. Prior research utilizing a very similar sample has demonstrated that this is a valid method to collect these data (i.e., self-reported SMU highly correlates with objective measures; Tuck & Thompson, 2021).

Self-Promotion Impression Management. We measured the extent to which individuals engage in self-promotion with the self-promotion subscale of the Impression Management Styles Scale (IMS; Bolino & Turnley, 1999). This subscale consists of four items scored from 1 (*never behave this way*) to 5 (*often behave this way*). A sample item includes "make people aware of your accomplishments." The IMS was developed in a student sample with internal consistency for items in the self-promotion subscale ranging from good to excellent (α = .88–.92; Bolino & Turnley, 1999). Internal consistency in the current sample was good.

Social Anxiety. We assessed social anxiety with the Social Interaction Anxiety Scale (SIAS; Mattick & Clarke, 1998) with reverse scored items removed, as recommended by Rodebaugh et al. (2006). The SIAS is scored on a Likert-type scale from 1 (*not at all*) to 5 (*extremely*), and this scale has been validated in college student samples (Mattick & Clarke, 1998; Rodebaugh et al., 2006). A sample item includes, "I worry about expressing myself in case I appear awkward." Internal consistency of items in the current sample was excellent.

Social Domain Security. We assessed the extent to which individuals feel secure in their position in the social world with the secure non-striving subscale of the Striving to Avoid Inferiority Scale (SAIS; Gilbert et al., 2007). This subscale consists of 12 items scored from 1 (*never*) to 4 (*always*). A sample item includes, "I don't feel under pressure to prove myself to others." Items in this subscale have demonstrated acceptable internal consistency (α = .69; Gilbert et al., 2007), and internal consistency in the current sample was excellent.

Life Satisfaction. We measured life satisfaction with the Satisfaction with Life Scale (Diener et al., 1985). This scale contains five items scored from 1 (*strongly disagree*) to 7 (*strongly agree*) and has been developed and used in numerous college student samples (e.g., Pavot & Diener, 2009). A sample item includes, "in most ways my life is close to my ideal." Internal consistency of items in the current sample was good.

Analytic Plan. To determine whether the factor structure replicated, we first conducted a confirmatory factor analysis for Model 3 (i.e., image-based, comparison-based, belief-based, and consumption-based SMU) using ratings on the 18-item and 17-item scale administered, choosing the version with the best fit. As in Study 2, all analyses were conducted in R Data Analysis Software (R Core Team, 2022), with items treated continuously and with MLR estimation. None of the participants in Study 3 had missing SMU activity data. Again, we aimed to derive a model with a CFI > .90, an

RMSEA < .06, and an SRMR < .08 (Hu & Bentler, 1999; Schumacker, 1992). If model fit was deemed to be poor, we planned to conduct no further analyses.

If the model was deemed acceptable, we planned to again compute internal consistencies for each factor and correlations between factors. Item responding was deemed reliable if Cronbach's alpha was greater than .70 (Gadermann et al., 2012), and factors were determined to be distinct if their correlations with one another were less than .70 (Costello & Osborne, 2005).

To further establish convergent validity, we ended by conducting multiple regression analyses. Again, the standardized score for each of the assessed trait measures was predicted by standardized scores for all model factors. Resulting beta coefficients represented partial correlations between the trait measure and each factor.

Transparency and Openness. All raw data and analytic code for Study 3 have been made available through the Open Science Foundation (https://osf.io/6fxu4/).

Results

We first conducted a confirmatory factor analysis for the hypothesized four-factor model (image-based, comparison-based, belief-based, and consumption-based SMU) with the 18-item scale. Fit indices for this four-factor model (Model 3) indicated acceptable model fit (CFI = .91; RMSEA = .06; SRMR = .07). However, fit indices for the four-factor model with the 17-item scale indicated slightly better fit (CFI = .92; RMSEA = .06; SRMR = .06) than they did for the 18-item scale. Therefore, the 17-item version of the scale was chosen as the final version of the SMUS, and all subsequent analyses utilize the 17-item scale. Item loadings on primary factors in Study 3 can be found in Table 1.

Internal consistency for items in each factor in Study 3 was good (α = .77–.83; see Table 3). In addition, factor correlations ranged from small to moderate (r = .20–.55), indicating that although the factors are significantly associated, they are distinct from one another. We finally conducted multiple regression models for each trait measure predicted by all four factors. Partial correlations between the factors and trait variables are presented in Table 2. The unique associations between the four SMU factors and each trait measure in Study 3 are described in the discussion section below.

Discussion

The purpose of Study 3 was to determine whether the structure of our SMU scale would be best captured by a four-factor model of image-based, comparison-based, belief-based, and consumption-based types of use. Results confirmed our four-factor model had good fit. Like in Study 2, items in each of these four factors had good internal consistencies, and each factor was distinct from one another. The final 17-item SMUS can be found in the Appendix.

Like in Study 2, image-based SMU was uniquely associated with exhibitionism narcissism. In addition, this type of use was positively related to a self-promotion impression management style, supporting the notion that image-based SMU is capturing what it claims to. Evidence for convergent validity was therefore retained. Contrary to expectations, image-based SMU was not significantly uniquely associated with increased social anxiety or decreased social domain security. This suggests that being motivated to impress others on SM is not necessarily associated with feeling insecure in one's social standing. In addition, image-based SMU was uniquely associated with greater frequency of SMU, which is not surprising given several of the items making up this factor require individuals to check their SM (e.g., "Looked at how many people liked, commented on, shared my content, or followed/friended me"). Taken together, this type of SMU is best described as a desire to make good impressions in the social world. Its associations with exhibitionism narcissism lead us to speculate that doing so may make individuals feel good about themselves.

All significant unique associations between comparison-based SMU and trait measures replicated from Study 2 to Study 3, retaining evidence for convergent validity. Namely, comparison-based use was uniquely associated with lower self-esteem, greater depression, fear of negative evaluation, social physique anxiety, need for approval, and negative emotionality. In addition, comparison-based SMU was significantly uniquely associated with social anxiety and social domain security (negatively), contrary to our expectations that these two traits would share their associations with image-based use. Nevertheless, these findings once again demonstrate that comparison-based SMU is associated with traits related to poorer social and emotional well-being. We again speculate that more comparison-based SMU may be associated with attempts to emotionally regulate for social and putatively maladaptive emotional purposes.

All significant unique associations between belief-based SMU and various trait measures that were found in Study 2 replicated in Study 3. That is, belief-based SMU was uniquely associated with poorer self-esteem, greater depression, a contra-hedonic emotion regulation style, concurrent low levels of agreeableness and conscientiousness, increased boredom susceptibility, and propensity to engage in drama. These associations again show support for convergent validity. Furthermore, belief-based SMU was significantly uniquely associated with increased frequency of SMU. Interestingly, this type of SMU was the only one shown to be uniquely associated with (decreased) life satisfaction. These findings provide further support that belief-based SMU is associated with traits related to poorer emotional well-being and potentially maladaptive social functioning.

Regarding consumption-based SMU, the only unique trait association that replicated from Study 2 to Study 3 was a positive relation with enjoyment on SM, which is supported by literature and shows support for convergent validity. As expected, consumption-based SMU was uniquely associated with our newly administered assessment of time per day spent on SM and frequency of SMU in Study 3, lending support that this style of SMU may be capturing general use well. Consumption-based use was not uniquely significantly related to greater self-esteem, lower depression, and less contra-hedonic emotion regulation goals, as it was in Study 2, possibly due to the initial correlations being small in magnitude. Generally, consumption-based SMU was positively related to traits reflecting psychological well-being and negatively related to traits reflecting ill-being in Study 3, but these relations were small and insignificant. Therefore, consumption-based SMU appears to generally capture people's enjoyment and use of SM.

For each type of SMU, there were significant partial correlations with trait measures that did not replicate between Studies 2 and 3. There are two likely reasons for non-replication. First, the associations that did not replicate were generally small in magnitude. Second, it is possible that variance in a trait measure was better accounted for by one type of SMU in one study and less accounted for by the same type of SMU in the other. As variance in the types of SMU varied from one study to the next, so did multivariate associations.

General Discussion

Despite growing interest and research on SMU, until now, there has not been an empirically developed SMU measure that was developed through assessment of a comprehensive list of SM activities or that can be used across different SM platforms. By designing such a measure, we sought to create a new instrument that could be used to classify nuanced categories of SMU. Our findings point to a novel four-factor model of SMU that provides more nuance than the conventional categorization of passive versus active use or frequency of use. These factors include image-based, comparison-based, belief-based, and consumption-based SMU.

To summarize, image-based SMU consists of activities related to how one is viewed by others. Across Studies 2 and 3, image-based SMU was associated with traits indicating a desire to make good impressions in the social world. Comparison-based SMU consists of activities related to comparing oneself to others and to one's own past. Again, across both studies, comparison-based use was associated with traits related to poor social and emotional well-being. Belief-based use consists of activities related to feeling and expressing one's negative beliefs and opinions on topics. Across Studies 1 and 2, belief-based SMU was shown to be associated with traits related to poorer emotional well-being and potentially maladaptive social functioning and regulation. Consumption-based SMU consists of activities related to consuming SM content. In both studies, consumption-based SMU was associated with broad use of SM and SM enjoyment.

Our hypothesized model (Model 1) consisting of two categories of active use and two of passive use was not supported. Furthermore, a model testing the conventional categorizations of active social, active non-social, and passive SMU (Model 2) did not fit the data well either. The fact that the data driven approach taken in these studies did not support conventional nor newer conceptualizations of passive versus active SMU holds important implications for how the field should understand and define SMU. Indeed, while belief-based SMU contains several items that would conventionally group into an active category, it also contains an item that would conventionally be viewed as quite passive (i.e., "Sought out content that I morally or ethically disagreed with"). Furthermore, while the idea of using SM for the purposes of media consumption, social comparison, and impression management has conventionally been thought of as composing one passive category of use, our data show that these three types of use are distinct, composing consumption-based, comparison-based, and image-based SMU, respectively. The items that compose these conventionally passive forms of use also contain some items that would be conventionally viewed as active (i.e., "Made/shared a post or story about something positive that was personally about me"). Taken together, these findings underscore that SMU is not best conceptualized as active versus passive. Instead, SMU appears better classified into groups reflecting people's attempts to share and feel their beliefs (i.e., belief-based SMU), make social comparisons (i.e., comparison-based SMU), manage their social image (i.e., image-based SMU), and consume content (i.e., consumption-based SMU).

The elucidation of image-based and comparison-based as distinct types of SMU is particularly noteworthy. As previously noted, multiple investigators have speculated that SM can facilitate social comparison (i.e., comparison-based SMU) and impression management (i.e., image-based SMU), hypothesizing that this may explain why passive SMU is associated with elevated depressive symptoms (i.e., that individuals naturally engage in social comparison and impression management when using SM passively; e.g., Zhu & Bao, 2018). According to our findings, however, consumption-based SMU (i.e., passive use) is a distinct construct from image-based and comparison-based SMU. In fact, while image-based and comparison-based SMU were each associated with traits suggesting poor social and/or emotional well-being (e.g., narcissism, depression), consumption-based use was associated with traits related to greater psychological well-being (e.g., agreeableness, self-esteem). In addition, our findings suggest that image-based and comparison-based SMU are distinct constructs that are uniquely associated with various traits; when examining significant partial correlations with trait measures, we found no overlap between image-based and comparison-based SMU, and these two factors only moderately correlated with one another. While much of the literature has discussed impression management and social comparison as processes that jointly arise when individuals engage in conventionally passive SMU, our data suggest that these types of use are distinct.

These findings provide a structure for understanding what are likely adaptive versus maladaptive types of SMU and highlight possible clinical implications of this work. For instance, engaging in more belief-based SMU is associated with experiencing negative emotional and social outcomes, whereas engaging in more consumption-based SMU is associated with greater enjoyment from SMU. Our findings suggest that mental health providers should consider assessing how their clients engage in SMU and how this may influence and be influenced by other clinically relevant constructs (e.g., depression, emotion regulation difficulties). By helping clients understand how they engage in SMU and how SMU may be implicated in psychological well-being, mental health providers can also help guide clients toward healthier patterns of use. Our found factor structure and assessment tool provide the framework for clinicians to begin having these important conversations.

We examined how each factor was related to trait measures while accounting for the three other types of SMU. Some factors showed similar unique associations with the same trait measures (e.g., low self-esteem was uniquely associated with both comparison and broadly active SMU). It will be important for future research to explore how these types of SMU are uniquely associated with various traits. For instance, we hypothesize that belief-based SMU is uniquely positively associated with trait levels of anger and pride, whereas comparison-based SMU is uniquely positively associated with trait levels of sadness and negatively associated with pride. If our hypotheses were supported, this would provide evidence of discriminant validity. In addition, by continuing to examine how these types of SMU uniquely correlate with people's traits, more can be learned about individual differences regarding different forms of SMU.

Relatedly, it will be important for future research to continue examining how these types of SMU are associated with various emotional experiences. For instance, an intriguing question rests in whether individuals' emotional state when starting to use SM predicts how they choose to use SM. One might predict, for example, that someone experiencing a low mood may be more likely to engage in comparison-based use, the style of use consistently associated with depressive symptoms and low self-esteem. There is additionally a dearth of research on how individuals' use of SM prospectively predicts their emotion. The few studies that exist have yielded inconsistent findings, with some finding associations between SMU and momentary positive emotion (Lin & Utz, 2015) and others with momentary negative emotion (e.g., Willoughby et al., 2020). We propose that these mixed findings may be explained, at least in part, by the ways in which individuals use SM. For instance, we predict that using SM in a consumption-based way is more likely to result in positive emotions than using SM in a comparison-based way since consumption-based use is associated with greater enjoyment on SM while comparison-based use is associated with constructs like low self-esteem. Future research could directly examine these hypotheses by manipulating emotional states and how individuals use SM, respectively, before participants engage in SMU.

Given the cross-sectional nature of this work, the question remains as to the causal nature of SMU on psychological well-being. Future work would benefit from longitudinal studies in addition to designs utilizing ecological momentary assessments (EMA). Such methods could determine whether engagement in a certain type of SMU at one time predicts emotion and psychological well-being at another. Of course, EMA studies, in particular, would necessitate modifying the scale to be used over a briefer time period than 1 week. In addition, these designs would help assess if certain types of SMU prospectively predict changes in depression and social anxiety symptomatology, a gap in knowledge that is frequently discussed and poorly understood. Examining how our four nuanced categories of SMU are associated with psychological well-being in these ways may help to inform healthy ways of using SM, and with this information, we may be able to help individuals form healthier SM habits.

Notably, few participants in this investigation reported using LinkedIn or Tumblr. This is consistent with statistics on use of SM in young adults (Pew Research Center, 2021). The only difference in young adult use of SM platforms compared with middle and older adults is those later in life use less Snapchat and more LinkedIn (Auxier & Anderson, 2021). Furthermore, TikTok was not one of the platforms participants were instructed to use because we wanted to ensure variability in the SMU activities reported by participants in the study. We expect that the SMUS will characterize use on TikTok, LinkedIn, and Tumblr because the scale captures SMU activities that apply to all SM platforms including these. However, future research is needed to further test these assertions.

We also acknowledge that direct messaging was not a component of SMU considered in the current study. Our reasoning for this was twofold. First, direct messaging is not unique to SMU (e.g., Instagram direct messages serve the same function as SMS text messages). Furthermore, the inclusion of direct messaging would have added additional nuances outside the scope of our quest to examine the factor structure of SMU, such as examining what content is being discussed (e.g., sharing positive versus negative experiences) and with whom. While these types of questions related to direct text communication are interesting and could shed light on interpersonal dynamics, they are not relevant to the factor structure underlying how people uniquely engage in SMU. Researchers should be cognizant of the fact that direct messaging is not a function of SMU included in the SMUS.

More broadly, future research should assess the psychometric properties of the SMUS among additional groups. For example, although college students represent the largest adult group to engage with SM, as many teenagers report using these platforms (Anderson & Jiang, 2018). Since both these groups grew up with SM in a similar day-in-age, we anticipate that our factor structure will represent the data well in a teenage sample, but of course, this awaits investigation.

SMU has been largely understudied in middle aged and older adults. We do not think older (and middle aged) adults engage in activities on SM that were not captured on our scale. However, we hypothesize that they may engage in these activities in a more heterogeneous manner than do college-aged adults because older (versus younger) adult samples have been found to struggle to navigate SM platforms (e.g., H.-Y. Wu & Chiou, 2020). For instance, older adults who are more technologically savvy may be more likely to post content about their grandchildren's accomplishments (image-based SMU), whereas others who are less technologically savvy may be more likely to simply look at posts about their grandchildren (consumption-based SMU). These examples demonstrate how the frequency of engagement in different types of SMU may differ across age groups, but that the factor structure of SMU itself could still look similar across ages. Of course, these are hypotheses that await future empirical investigation.

We aimed to create items in the SMUS that would be flexible to the evolving nature of SM. This said, it is possible that new SMU activities will arise over time that are not captured in our scale or that the activities currently captured will one day become obsolete. As such, researchers should keep this concern in mind when choosing an SMU measure, and we expect that all SMU measures will need to be modified over time to reflect any significant changes in SMU.

It is important to assess *how* individuals use SM when conducting SM research, and the SMUS serves as a nuanced measure of SMU. The SMUS will allow researchers to more easily capture distinct types of SMU that better reflect the structure of SMU. We are hopeful that this validated measure of different types of engagement in SMU will serve as a common tool that researchers can use, minimizing inconsistent findings in the field. Future research should examine how the types of SMU captured by the SMUS are associated with long-term psychological outcomes. We think that doing so will begin to present a clearer picture of the ways in which SMU influences the psychological well-being of the countless people who use SM across the globe.

Appendix

Social Media Use Scale (SMUS)

Directions. Please indicate how frequently you have engaged in each of the following social media activities in the PAST WEEK (7 days). Please only include activities engaged in on social networking sites such as Instagram and Facebook. Do *not* include activities related to direct messaging such as Facebook Messenger and Instagram direct messages. For each activity, please use the following scale:

Never	1–2 times per week	3–4 times per week	5–6 times per week	Once daily	2–5 times daily	6–9 times daily	10–13 times daily	Hourly or more
1	2	3	4	5	6	7	8	9

_____ 1. Made/shared a post or story about something positive that was personally about me
_____ 2. Looked at how many people liked, commented on, shared my content, or followed/friended me
_____ 3. Read comments to my own content
_____ 4. Edited and/or deleted my own social media content
_____ 5. Played with photo filtering/photo editing
_____ 6. Compared my body or appearance to others'
_____ 7. Compared my life or experiences to others'
_____ 8. Reminisced about the past
_____ 9. Made/shared a post or story about something negative that was personally about me
_____ 10. Made/shared a post or story about something negative that was NOT personally about me
_____ 11. Commented unsupportively or disliked/"reacted" unsupportively on other's post(s)
_____ 12. Sought out content that I morally or ethically disagreed with
_____ 13. Scrolled aimlessly through my feed(s)
_____ 14. Looked at others' stories
_____ 15. Navigated to others' profiles in my social network (e.g., friends or friends of friends)
_____ 16. Navigated to others' pages who I do not know (e.g., influencers or other famous people)
_____ 17. Watched videos such as memes, news content, and how-tos/recipes.

Scoring Instructions. Items should be presented in random order. There are four social media use subscales. The items for each subscale should be averaged. There are no reverse-keyed items.

Image-Based (5 items): 1, 2, 3, 4, 5
Comparison-Based (3 items): 6, 7, 8
Belief-Based (4 items): 9, 10, 11, 12
Consumption-Based (5 items): 13, 14, 15, 16, 17

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Data Availability Statement

Part of this study's design and hypotheses were preregistered; see https://osf.io/6fxu4/. Quantitative raw data and analytic code have been made available through the Open Science Foundation (https://osf.io/6fxu4/).

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Supplemental Material

Supplemental material for this article is available online.

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