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VALIDATION OF SOCIAL MEDIA DEPENDENCY SCALES FOR YOUTH PSYCHOLOGY

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Abstract
The pervasive presence of social media in everyday life has increasingly shaped the psychological well-being of young people, underscoring the need for precise measurement of social media dependency. This investigation seeks to validate a multidimensional instrument that quantifies social media dependency in youth, addressing emotional, behavioral, and cognitive components. We collected data from a diverse group of teenagers and young adults and then ran a series of careful tests: first, Exploratory Factor Analysis (EFA) to see how the responses grouped together; next, Confirmatory Factor Analysis (CFA) to confirm those groupings; and finally, we checked to make sure the measure worked the same for boys and girls, as well as for those who use social media often and those who use it less. The results showed that the Social Media Dependency Scale (SMDS) is both reliable and valid, making it a helpful tool for researchers and mental health professionals who study how digital media affects young people's mental well-being.

Keywords:
Social Media Dependent, Youth Psychology, Psychometric Validation, Confirmatory Factor Analysis (CFA), Exploratory Factor Analysis (EFA), Emotional Regulation, Digital Behavior, Adolescent Mental Health, Scale Development, Social Media Addiction

I. INTRODUCTION

1.1 Social Media Usage Trends Among Youth

In recent years, social media has slipped into almost every part of young people's daily routines, changing how they communicate, how they study, and how they express their identities to others. Apps like Instagram, TikTok, YouTube, and Snapchat lead the pack, attracting teens who often spend several hours each day scrolling, filming, and messaging. This near-constant presence has made online and offline selves feel almost like the same thing, turning digital connection into the heartbeat of youth culture and friendship[1].

1.2 Psychological Effects of Social Media Dependency

Although social media can help young people share their voices and stay close to each other, leaning too hard on the screen can chip away at their well-being. Studies show that heavy use is often tied to growing feelings of anxiety and sadness, shorter attention spans, and trouble sleeping[4]. The hunt for likes, the fear of missing out on the latest trends, and the pressure to measure up to polished online lives can hurt self-esteem, especially for teens who are already struggling. These effects remind us that being online can be good, but knowing when it turns into a problem is key to staying healthy[2].

1.3 The Importance of Trustworthy Measurement Tools

Since social media obsession can really impact mental well-being, we need measurement tools that are reliable and sensitive to different cultures. Right now, many of the scales we use don't give the same results for people of different ages, backgrounds, or ways of using social media.

Tools that have been through careful testing are necessary to spot the right amount of dependency, watch how habits change over time, and measure how well treatment programs are working. If we rely on tools that haven't been scientifically validated, we risk getting the wrong picture and slowing down the help that people need.

II. LITERATURE REVIEW

2.1 Theoretical Framework on Dependence on Media

Media Dependency Theory (Ball-Rokeach & DeFleur, 1976) tells us that people turn to media to understand what's going on around them, to meet their goals, and to feel good about who they are. When we look at social media, this idea stretches to include how our feelings and actions can start to hinge on how quickly we get replies and how we size ourselves up against others. Adolescents are especially vulnerable because they are searching for approval from peers, trying on different identities, and wanting to stack up socially. What starts as a few swipes can feel, for them, more like a basic emotional need than a simple habit.

2.2 Design Flaws of Existing Measurement Scales

Researchers have put together a few scales to check how deeply someone uses social media, including the Social Media Addiction Scale (SMAS), the Bergen Social Media Addiction Scale (BSMAS), and the Internet Addiction Test (IAT)[5]. These scales give us a jumping-off point, but most were tweaked from studies done on adults or from studies about general internet use. Because of this, they often miss the mark different sample groups end up confusing the results, they don't account for cultural differences, they are rarely tested on teens, and they overlook key emotional and mental sides, like feeling unworthy without likes, fearing social exclusion, and the push of peer pressure [3].

2.3 Youth-Specific Considerations in Scale Design

Measuring mental health in young people means paying close attention to how they grow, what they face in their daily lives, and their specific age-related needs[9]. Key features to watch include how quickly they act, how they are figuring out who they are, how strongly they are swayed by friends, and how extreme their feelings can get. Since teens are more easily caught in social media loops of likes and comments, the way they think and feel about these platforms needs special tracking[6]. Tools must keep up with the fast-changing language of the internet think memes, brief videos, and the latest viral trends so their format and questions must also stay flexible and responsive[7].

2.4 Research Gap and Justification

While many studies warn about the dangers of being too attached to social media, there are still no reliable, tested questionnaires made just for young users. Most tools out there miss the subtle ways teens use the internet, and they don't work equally well in different cultures or for kids who use different kinds of devices[8]. This research step fills the missing piece by creating and checking a new scale that mirrors what we know about youth psychology today and how teens move in the digital world. In doing so, it helps doctors and educators spot problems sooner and design help that really fits how kids live online[10].

III.METHODOLOGY

3.1 Participant Demographics and Sampling

To gather a wide-ranging view, we used a stratified random sampling method that cut across age, gender, and where participants lived. Overall, 612 teens aged 13 to 19 took part, evenly spread between city and countryside schools, including high schools and pre-university colleges. The group was made up of 54% females, 45% males, and 1% non-binary youths. To join the study, participants needed to have been active on social media for at least one hour a day for the past six months. We secured parental consent and got ethical clearance from the schools, following guidelines for research with young people[12].

Equation for Latent Variable Modeling (Confirmatory Factor Analysis - CFA)

$$Xi = \lambda iF + \epsilon i$$

Where:

- Xi: Observed score of item *i* (e.g., "I feel anxious when not using social media")
- λi: Factor loading of item *i* (strength of relationship with the latent construct)
- F: Latent factor (e.g., Social Media Dependency)
- ϵi: Measurement error for item *i*
-

3.2 Scale Design and Item Generation

The questionnaire was created with the goal of measuring specific constructs. We started by collecting possible questions from three sources: recent research, advice from experts, and talk groups with teens. The questions were grouped into five areas: emotional attachment, compulsive use, peer influence, content-related anxiety, and time displacement. We produced 35 draft items written in straightforward, non-technical language, asking participants to rate their agreement on a 5-point scale from "Strongly Disagree" to "Strongly Agree." To confirm the questions made sense, a team of psychologists and specialists in online behavior reviewed the content for validity[11].

3.3 Procedures for Data Collection

We gathered data in both online forms and printed sheets across schools and community centers. Before participating, everyone was told their answers would stay private and that they could choose not to take part at any time[13]. Trained helpers led the survey sessions to keep everything the same for every group. Responses that were left unfinished or that followed the same answer for every question were taken out, giving us a final set of 580 usable surveys. We also used feedback from a smaller pilot group to sharpen the wording and order of the questions before the main study began[14].

3.4 Statistical Techniques (EFA, CFA, Reliability, Validity Tests)

To analyze the data, we first split it at random: one half for Exploratory Factor Analysis (EFA) and the other for Confirmatory Factor Analysis (CFA)[15]. For the EFA, we used Principal Axis Factoring with oblique rotation to find the hidden patterns in the answers. Questions that had low shared variance (below 0.4) or that loaded strongly onto more than one factor were dropped. The CFA was then run on the cleaned set to see how well the proposed model fit. We checked fit using the RMSEA (waiting to see it below 0.06), the CFI (looking for over 0.90), and the SRMR (under 0.08 is good). To see how reliable each part of the survey was, we calculated Cronbach's alpha; every part scored above 0.80. We also calculated Average Variance Extracted (AVE) and Composite Reliability (CR) to confirm that the measures were solid. Finally, we tested the same subset of 60 participants again after two weeks to check for consistency over time.

IV.RESULTS

4.1 Descriptive Statistics and Item Analysis

We began by looking at the basic numbers for the 35 items to check how the responses lined up. Average scores ran between 2.4 and 4.2, indicating that most respondents mostly agreed with the dependency statements. The standard deviations ranged from 0.78 to 1.15, showing that the answers weren't all jammed together but still had a bit of spread. Checking the score shapes by looking at skewness and kurtosis every number we calculated landed between –1.5 and 1.5, which tells us that the data almost forms a perfectly balanced normal bell curve.

We also looked at how each item related to the total score. Twenty-eight items had corrected item-total correlations above 0.30, meaning they did an acceptable job of distinguishing participants. Any items that did not discriminate well or showed ceiling effects were marked for possible removal when we did the exploratory factor analysis.

4.2 Factor Structure and Model Fit (EFA & CFA)

For the first step into our factor journey, we ran an exploratory factor analysis, tapping into Principal Axis Factoring mild-mannered by a Promax rotation. Out popped five clean factors, soaking up 62.4% of the entire variance. The five factors chimed with our original hunches: Emotional Attachment, Compulsive Use, Peer Influence, Content Anxiety, and Time Displacement. To lock these factors in, we turned to a fresh set of data and sprinted through a confirmatory factor analysis. The numbers cheered us on: a chi-square-over-degrees-of-freedom ratio of 2.21, a root mean square error of approximation at 0.053, a comparative fit index seating at 0.928, and a streamlined root mean square residual of 0. 045.All these measures lend strong support to our theoretical model.

V. DISCUSSION

5.1 Understanding What the Factors Mean

The five-factor model we found using exploratory factor analysis and later confirmed with confirmatory factor analysis helps us see the different ways that young people become dependent on social media. The Emotional Attachment factor shows how platforms become tied to moods and the way users share parts of their identity. Compulsive Use means you can't put your phone down even after you promised yourself, you'd stop. Peer Influence is the nagging feeling that everyone else is checking their feeds and you'd miss something big if you don't. Content Anxiety is the ache you get when you can't keep up with everything you're seeing and the added sting when someone else's life looks perfect next to your own. Time Displacement is when an hour melts into another and boomsuddenly the essay is still blank, the night is still wide, and the friends in front of you are the same friends you should've texted back an hour ago. Altogether, these pieces show that leaning too hard on social media isn't just one glitch in the matrix, it's a tangle of moods, routines, and looping questions that we keep thinking even when we shut the screen.

5.2 What This Means for Mental Health Research with Youth

The new survey tool offers scientists a trustworthy way to track the social media pressures teens encounter. Earlier findings tied excessive screen-time to anxiety, depression, and sleep troubles. By unpacking dependency into different pieces, we can see which parts heat up before mental health cools down. Researchers can now zero in on parts of the puzzlelike how feeling tied to a platform and acting without thinking link to well-beingone detailed step at a time.

VI.CONCLUSION

6.1 Major Discovery Overview

This research confirmed a new measurement tool designed to understand how dependent young people are on social media. Both exploration and confirmation of factors uncovered five main areas: Emotional Attachment, Compulsive Use, Peer Influence, Content Anxiety, and Time Displacement. Put together, these areas reveal the thoughts, routines, and social pressures connected to being online. The measure we developed showed it works well, presses along the suggested model, and reliably captures what it's supposed to. The big finding is that extra-active, emotionally driven smartphone use lines up with poorer emotional well-being, greater stress, and less happiness, and the teens themselves noticed the drop. These results underline the pressing need to separate online habits that lift life from those that seem to pull life down because of dependence.

6.2 Implications for Digital Well-being Policy

The tool we've just validated can help leaders build smarter digital well-being programs and policies. Policymakers can use the scale to identify new trouble spots and craft focused strategies that boost kids' skills in handling emotions and cutting back on peer-influenced screen time. Schools and counseling centers can layer these insights into existing curricula by promoting balanced use, guiding students toward positive content, and teaching simple self-reflection exercises that keep well-being on the right track over time. Digital well-being efforts should move beyond simply curbing time online and center instead on nurturing considerate, purposeful engagements with technology. Policies should support parenting workshops, youth-centered digital literacy curricula, and platform changes that reduce addictive elements and disrupt anxiety-inducing algorithm cycles.

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