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IDENTIFYING FACTORS AND THE RELATIONSHIP BETWEEN WITHDRAWAL, COMPULSION AND ANXIETIES IN INSTAGRAM USERS

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INTRODUCTION

Nowadays, social media platforms are one of the most popular and widely used applications on the Internet (Kırcaburun et al., 2019). Also known as social networking sites (or SNSs), they are websites and applications that allow users to edit and share content with networks (i.e., friends, acquaintances, etc.) built by themselves. According to Boyd and Ellison (2007), SNSs are Internet applications that allow people to create a public or semi-public profile inside a bounded system, interact with a list of other users, and view profiles of their list of connections and those made by others within the system. SNSs revolutionized the way people interact with each other. Its usage has dramatically increased in the decade, coinciding with the rise in adults who own smartphones – thus enabling social networking to happen anytime and anywhere. Users can access social media on different platforms (mobile or computer devices) for various activities.

Social media affords multiple types of communication, enabling interactions among users through self-presentation and interpersonal exchanges (i.e., one-to-one messaging) or concurrently mass (i.e., one-to-many messaging). It can include meaningful exchanges such as messages inside social support groups or private sharing between close friends and family (Hayes et al., 2016). Although social media platforms can be used for positive purposes such as maintaining relationships, meeting new people, socializing, and informational and educational purposes, some individuals can also demonstrate problematic online behaviors that negatively impact them (Kırcaburun et al., 2019).

The Uses and Gratifications approach settles that consumers are active in their choice of media and engage with certain technologies to fulfill specific needs. In general, gratification needs guide media consumption habits. Facebook, the best-established social media platform, is geared towards having fun and knowing what is going on in one's social network, having two primary motivating factors of use: the need to belong and the need for self-presentation. Its photo-sharing and messaging functions have mainly been replaced by more specialized applications such as Instagram and Snapchat; both SNSs focused on sharing aesthetically-filtered photos or videos. Though unclear what role these images play in attending specific needs, users share photos to gratify the need for affection and attention, social influence, habit, disclosure, and information sharing (Pittman & Reich, 2016).

Initially released in 2010, Instagram is now one of the most-used social platforms with roughly 1.2 billion monthly active users. Instagram allows them to choose whom to follow, post photos and videos, search content and products, privately message with other users, amongst various other resources. Researchers have suggested that, in contrast with other SNSs, Instagram focuses more on self-presentation and promotion than maintaining and building relationships. The primary activity on Instagram is to share photos and short videos, which involves engaging in visual self-presentation, and viewing content from others (Dumas et al., 2017).

Previous studies on social media, particularly Facebook, have yielded mixed results but mainly highlighted negative implications of passive forms of SNS use (Lup et al., 2015). Some of Instagram's features also characterize as passive SNS, making people more vulnerable to harmful mental health effects. The #StatusOfMind survey, published in 2017 by the United Kingdom's Royal Society for Public Health, reported Instagram as the most detrimental social media platform after enquiring almost 1,500 young people about issues such as anxiety, depression, loneliness, sleep, body image, bullying, fear of missing out (FOMO), and others.

However, as well as other SNSs, it received positive scores for self-identity, self-expression, community building, and emotional support.

The World Health Organization (WHO), in 2018, indicated that in Brazil, 5.8% of the population (equivalent to 11.5 million people) suffered from depression linked to mental illnesses and 9.3% (equivalent to 18.6 million people) from anxiety disorders, based on excessive media consumption, which is higher than the world average of 4.4% (322 million people) for depression and 3.6% from anxiety disorder (263 million people). In Latin America and specifically in Brazil, few studies have been done on the use of the Internet related to mental health problems (Vasconcelos et al., 2015).

In this context in which the coronavirus pandemic boosted social media usage globally, asides from aiding in disseminating educational content and information about COVID-19, SNSs have become an important tool to bring people closer while they cannot meet physically.

All the aspects raised above bring concerns and motivations that can be summed up to the problem of this research, which is **how does problematic Instagram use affect social anxieties?**

Given the relevance of this social problem, the main objective of this research is to identify the factors and the relationship between Problematic Social Media Use and Anxieties in Instagram Users. Specific objectives include identification of the primary mental health effects caused by Instagram, analysis of the impact of various features for each mental health effect, identification of the behavior on Instagram by generation, and presenting a framework that relates behavioral and attitudinal variables to mental health effects.

This research contributes to the development of a psychometric analysis with six adapted effects on mental health evidenced in the literature. The following scales were used: for Social Anxiety Scale for Social Media Users (SAS-SMU) (Alkis et al., 2017) and the Social Media Use Questionnaire (SMUQ) (Xanidis & Brignell, 2016).

THEORETICAL FRAMEWORK

This session is formed by the theories supporting the choices of variables for this study's construct, as well as its definitions and relevant data for the proposed framework.

Mental health on Instagram

Mobile SNS provides its users with constant access to posts created by others and enables individuals also to assume the role of creator, sharing content with friends, acquaintances, and other online audiences. Like other SNS such as Facebook and Twitter, Instagram posts collect feedback as "likes" and comments (Fox & Vendemia, 2016). Despite requiring little investment of time or energy from the liker, these quick responses carry complex social meaning and serve as powerful self-assessment tools (Butkowski et al., 2019). Users receive direct reactions to their own social media posts and witness the ones received by others. In such interactions, likes and comments serve as quantified social acceptance measures and, when viewed as the most important, immerses users in searching for validation (Butkowski et al., 2019). Such intertwined users' roles as both consumers and creators encourage social comparison and observational learning, influencing the content and its editing (Chae, 2017).

Excessive or indiscriminate use of the Internet, including social networks, can negatively affect personal relationships, in communication with the external environment, and to unsatisfactory professional performance. It is suggested that time spent engaging with SNSs displaces other more critical activities beneficial to mental health, such as sleep and face-to-face time with friends. Many studies report associations between increased time spent on SNSs and heightened levels of depression and anxiety (Coyne et al., 2020). Additionally, research has shown that attitudes toward social media feedback received on selfies, an appearance-oriented self-representation, affect body image disturbance in young women (Butkowski et al., 2019).

Nonetheless, social media's popularity can also be a bright spot for mental health, with many positive aspects of virtual communication. Use of social media to strengthen pre-existing affective bonds is associated with decreased depression. Healthy use can also increase perceived social support and self-esteem, as well as decrease loneliness and depression (Shaw & Gant, 2002). Therefore, the benefits and detriments can be a matter of how social media is actually used.

Problematic Social Media Use

A now integral part of daily life activities, Internet use has reached such an extent that individuals started demonstrating behavioral and psychological patterns seen in other addictions such as drugs, gambling, or alcohol. Studies demonstrated that relying on SNS to address loneliness and stress or maintain and establish new relationships significantly predicted symptoms of dependence (Xanidis & Brignell, 2016).

Inconsistency exists around the definition of problematic social media use (PSMU). However, Bányai et al. (2017) comprises PSMU as mood changes and preoccupation of using social media, including negative feelings and psychological symptoms when they are unavailable, and facing negative consequences in real life areas caused by excessive use. Diagnosis of internet-related disorders has not been established due to a lack of constancy in empirical studies and many synonym suggestions of diagnosis. The Diagnostic and Statistical Manual of Mental Disorders (DSM-5) currently recognizes only one internet-related disorder – the Internet Gaming Disorder –, included in Section 3 of the DSM-5.

The most widely used definition is Davis' (2001), in which the acts of using the Internet to regulate unpleasant moods, perceiving more interpersonal control online than offline, and becoming attached to the benefits provided by the Internet lead to excessive use, compulsion development, withdrawal signs, and negative social, occupational and/or psychological consequences in the user's offline life. These factors are collectively thought to be symptomatic of PSMU.

This form of Internet addiction has no offline equivalent but causes similar symptoms as substance abuse deprivation does. When not connected to social media, individuals may feel isolated and stressed, leading to increased anxiety and depression (Kırcaburun et al., 2019). PSMU can then be determined by addictions symptoms that include: salience (i.e., preoccupation with social media use), mood modification (i.e., excessive social media use causing specific changes in mood states), withdrawal symptoms (i.e., negative feelings such as irritability or anxiety when social media use is restricted), conflict (i.e., interpersonal problems resulted by social media usage), and relapse (i.e., returning to excessive use after a period of abstinence) (Bányai et al., 2017).

There is a positive correlation between depressive symptoms and social media use and a negative one between self-esteem and high social media use (Bányai et al., 2017). Several psychological vulnerabilities are associated with PSMU, including depression, loneliness, substance addictions, aggression, and shyness. Since these factors move individuals to isolate themselves in their offline lives, they seek to fulfill interpersonal needs online (B. W. Lee & Stapinski, 2012). Subsequently, problematic social media use is a consequence of pre-existing psychopathology.

The **Social Media Use Questionnaire (SMUQ)** was developed to measure addiction behavior patterns and dependence, of SNS (social network sites) use. Xanidis and Brignell (2016) indicated a correlation between increased dependence on SNS and decreased sleep quality, and increased everyday cognitive failures. It has since become an important tool to assess problematic and excessive use of social media.

Social Anxiety

Anxiety is a construct that reflects affective characteristics and involves cognitive, behavioral, and physiological aspects. It is a common disorder defined by worrying thoughts, feelings of apprehension, tension, nervousness, and even physical changes such as sweating, increased blood pressure, trembling, and dizziness. Social anxiety is a type of anxiety resulting from fear or anxiousness from interacting with or being negatively evaluated by others. It has been defined as the enduring experience of discomfort, hostile ideation, and incompetence performance in the anticipation and conduct of an interpersonal transaction and a state resulting from the prospect or presence of interpersonal evaluation in real or imagined social settings (Alkis et al., 2017).

Socially anxious people need to reduce anxiety, thus motivating them to minimize their chances of making undesired impressions on others. Severe social anxiety leads to isolation and social withdrawal (Y.-K. Lee et al., 2014). However, it can also appear in subtle safety behaviors such as speaking quickly or over preparation. Inflated threat expectancies in social-evaluative circumstances and their corresponding avoidance prevent individuals from realizing that they are overestimating the likelihood of negative feedback and underestimating their own social ability (B. W. Lee & Stapinski, 2012).

Due to greater control over self-presentation, improved relationship quality, and decreased risk of negative evaluation (B. W. Lee & Stapinski, 2012), there is an overall perception that online communication provides safer means of interaction. Research does show that online interaction positively benefits anxious individuals, but also puts this group as likely to develop problematic or excessive Internet use behavior (Y.-K. Lee et al., 2014). In opposition, the pursuit of attention and self-validation via Instagram likes can be positive because it provides individuals with a tool to try on and gain feedback on new facets of their developing identities, especially adolescents and emerging adults (Dumas et al., 2017).

This study considers four dimensions of Social Anxiety relevant to social media use, as per research by Alkis et al. (2017): Shared Content Anxiety (SCA), Privacy Concern Anxiety (PCA), Interaction Anxiety (IA), and Self-Evaluation Anxiety (SEA). SCA derives from the sharing of content by individuals themselves or by others about them in social media platforms and how others will judge these. PCA includes certain potential privacy risks regarding personal information disclosed on SNS. Individuals with deep privacy concerns and who are socially anxious are more likely to avoid revealing and sharing personal information online. IA refers to the social anxiety derived from interacting and communicating with someone, especially those who newly met on social media platforms. Lastly, SEA considers the way a person evaluates and views him/herself because of what other people thought about him/her on social media platforms.

The **Social Anxiety Scale for Social Media Users (SAS-SMU)** is a four-factor structured construct created by Alkis, Kadirhan, and Sat (2017) to measure social anxiety in social media platforms specifically. Studies that used the SAS-SMU have shown that higher social media addiction levels are associated with higher levels of anxiety and burnout (Liu & Ma, 2020). Moreover, negative assumptions about the world significantly predict higher levels of interaction anxiety and self-evaluation anxiety (Pitcho-Prelorentzos et al., 2020).

METHOD

Regarding the empirical phase of this study we conducted the application of a survey, in which the data collection instrument was composed of descriptive questions and assertions. The Likert scale used end points anchored at 1 and 5 for all statements. Descriptive questions were used to collect the respondents' characteristics, such as age, sex, and income. All scales were adapted for the context of this study. The confirmatory method was used using structural equation modeling based on covariance using the IBM SPSS v.25 and LISREL v.8.80 software.

Data collection and sample procedures

For the adaptation of the research instrument and the selected scales to the Brazilian context, we used a reverse translation process. Before applying the questionnaire, the instrument was sent to 4 judges for validation. After review for comprehension, clarity of the items, and relevance, a pre-test was performed with 27 individuals. After applying the test, 872 questionnaires were obtained using SurveyLab's platform. To prepare the database, outliers were identified and removed using the Mahalanobis Distance D^2 (Hair et al., 2010). This step resulted in removing 115 questionnaires, leaving a total of 757 observations in the sample. We carried out data collection by online means and the criterion for selecting the research subject was concerning the use of Instagram, with non-users being discarded. The questionnaire was also advertised to a vast audience via paid ads inside Instagram. Consequently, the sample can be classified as non-probabilistic for convenience and by judgment, for the exploratory function in opinion research about Instagram use (Malhotra, 2014).

Data analysis procedures

Due to the characteristics of the study, descriptive analyzes and three multivariate phases were conducted: a) Exploratory Factor Analysis - to identify the components of each of the groups of the scales under study (Social Anxiety and Problematic Social Media Use); and b) Structural Equation Modeling.

DATA ANALYSIS

Common Method Bias, Non-respondents Bias and Collinearity

To ensure that no systematic bias influenced the collected information, the Common Method Variance (CMV) was checked by applying Harman's one-factor test (Podsakoff and Organ, 1986) on the 28 items, and the variance extracted by the first component was 39.85%, lower than the minimum of 50%. In addition, the analysis of the bias of "non-respondents" was performed, according to Armstrong and Overton (1977), and it was found that both the common method bias and the non-respondents' bias were not a significant problem. As the sample was considered large, two random sub-samples were divided and the multigroup effect of latent variables was analyzed (T test). Both subsamples showed equivalent behavior, resulting in keeping the total sample. Late response bias was also examined by comparing early (first week) and late (last week) responses, and no statistical differences were seen between groups. When analyzing the collinearity, it was discovered that all the Variance Inflation Factors (VIFs) of the constructs were Compulsion=1.656, Withdrawal=1.446, SCA=2.710, PCA=1.349, IA=1.714, and SEA=2.770, indicating that there is no multicollinearity between the constructs. Therefore, we can assume that the regression coefficients are well estimated and suitable for the model.

Profile of respondents

This section presents the survey respondents' profile to characterize the sample, comprised of 757 people, all Instagram users, considering valid responses. As described in Table 2, there are 520 females (68.7%) and 237 males (31.3%). If we observe the relationship between sex and age, millennials stand out in both sexes, composed of 30.8% (n=105) male and 69.2% (n=236) female respondents. Both groups reported a similar frequency of SNS and Instagram use, with 32.7% (n=170) females and 35% (n=83) males using SNSs for over 4 hours per day and with 28.1% (n=146) of females and 28.7% (n=68) males using Instagram for over 2 hours per day. There was homogeneity between females and males regarding the motivation of Instagram use.

This study considers the chronological endpoints set by Pew Research Center, an American nonpartisan that conducts public opinion polling, media content analysis, demographic research, and other empirical social science research. Using their data, Generation Z respondents are aged 7 to 22, millennials 23 to 38, generation X 39 to 54, and boomers 55 to 73. By this division, the respondent distribution is 26.3% (n=199) generation Z, 45% (n=341) millennials, 21.4% (n=162) generation X and 7.3 (n=55) boomers. Income distribution showed that 64.6% (n=489) earn up to R$ 4,180.00 per month, with 59.2% (n=202) of millennials in the same range. Another 25.9% (n=196) of total respondents earn between R$ 4,180.01 and R$ 10,450.00, with 29.6% (n=101) millennials in the same range.

Millennials and generation X showed a higher daily frequency of use (n=163/66.3%) than other generations, with over 2 hours usage. Boomers use it less frequently, with an average between half an hour and an hour per day (n=22/40%). Most respondents older than 23 years old have been users for 5 to 8 years (n=264/34.9%). While 53.3% (n=106) of generation Z, 63.9% (n=218) of millennials and 57.4% (n=93) of generation X consider Instagram to be their main social media network, only 40% (n=22) of boomers agree.

Due to the timing and context of this study and for comparison purposes, participants were asked to classify their frequency of use in a 1-5 Likert scale during three distinct periods: before the pandemic, during early pandemic (e.g., first few months, when there was still a "feeling of newness") and now (after almost a year of its start). Results showed that all generations increased their frequencies of use (Figure 1). While Generation X ($\bar{x}_{before}$=2.77; $\bar{x}_{early}$=3.40; $\bar{x}_{now}$=3.96) and Boomers ($\bar{x}_{before}$=2.75; $\bar{x}_{early}$=3.13; $\bar{x}_{now}$ =3.98) had a more exponential increase of use as the periods progressed, Generation Z ($\bar{x}_{befor}$ =2.55; $\bar{x}_{early}$ =3.40; $\bar{x}_{now}$=3.55) and Millenials ($\bar{x}_{before}$=2.94; $\bar{x}_{early}$ =3.60; $\bar{x}_{now}$=3.76) stabilized theirs during the last two periods. Such behavior can be explained by the fact that early generations already had intensive use before the pandemic, while the two oldest got into SNSs more suddenly to stay connected during the social isolation period.

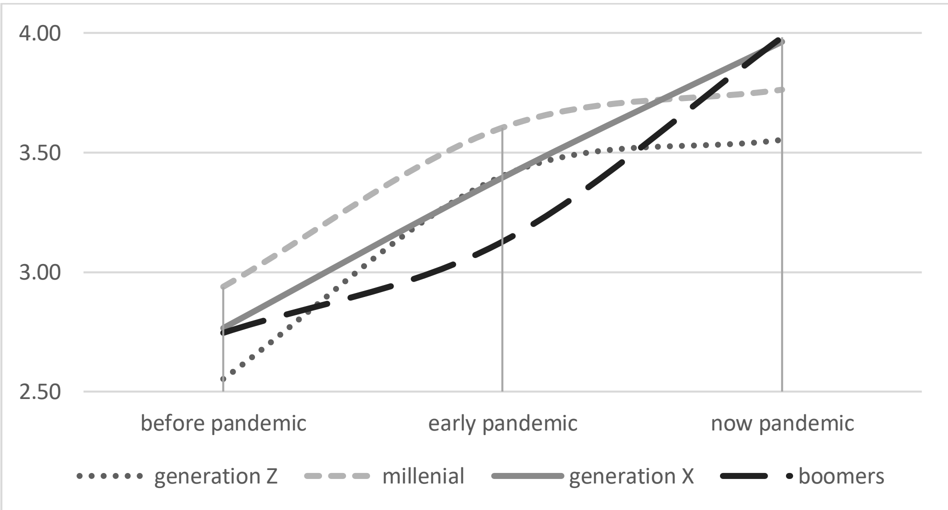

Figure 1: Comparison of frequency of use during three pandemic periods

Exploratory Factor Analysis (EFA)

In this phase, the variables that comprise the scales selected for this study were confirmed. Each of the scales underwent an EFA with its respective variables. The interest was primarily centered on the common factors, which are interpreted in relation to the observed variables (Hair et al., 2010).

The first analysis of the scales – Shared Content Anxiety, Privacy Concern Anxiety, Interaction Anxiety, Self-Evaluation Anxiety, Problematic Social Media Use – occurred through their respective commonality matrices. For this analysis, we used the Kaiser-Meyer-Olkin (KMO) criterion and the Bartlett Sphericity Test.

KMO values were verified, presenting a satisfactory result for all scales. In Bartlett's sphericity test, the result was significant for all scales, with $p<.001$. After these procedures, the cross-factor loading was observed, and some variables were excluded in the Social Media Use (SMUQ3 and SMUQ5) scale (see Appendix A).

Subsequently, unidimensionality (score>.50 in the factor) and low cross-load (score<.40 in the other factors) (Levin et al., 2013) were observed. All variables had adjustments due to commonality ($h^2<.5$) and weak coefficients (<.4). In the end, the loads were adjusted to one factor, for each of the observed scales, with adequate values for explaining the total sample variance, as well as the reliability, confirmed with Cronbach's Alpha (Table 1).

Table 1: Results obtained in the Exploratory Factor Analysis (EFA)

Effects on mental health	Scales	Scale Items	KMO	Sphericity test	Explanation of the total sample variance	α
Social Anxiety	SCA	7	.933	p<.001	72.21%	.935
	PCA	5	.796	p<.001	63.51%	.855
	IA	6	.890	p<.001	73.98%	.929
	SEA	3	.745	p<.001	83.61%	.902
Problematic Social Media Use	Withdrawal	3	.730	p<.001	76.85%	.848
	Compulsion	4	.825	p<.001	70.66%	.861

EFA resulted in the extraction of only one component for each of the psychological factors, which received the same names of origin, to facilitate the other analyzes of this research (Social Anxiety and Problematic Social Media Use). The latter was divided into two sub-scales, which the authors named Withdrawal (reflecting symptoms of abstinence from social media) and Compulsion (reflecting effects of actively engaging with social media in a problematic way). Measurement variables for the following analysis were constructed based on the respective averages of each component: Shared Content Anxiety ($\bar{x}$ = SCA1, SCA2, SCA3, SCA4, SCA5, SCA6, SCA7), Privacy Concern Anxiety ($\bar{x}$ = PCA1, PCA2, PCA3, PCA4, PCA5), Interaction Anxiety ($\bar{x}$ = IA1, IA2, IA3, IA4, IA5, IA6), Self-Evaluation Anxiety ($\bar{x}$ = SEA1, SEA2, SEA3), Withdrawal ($\bar{x}$ = SMUQ1, SMUQ2, SMUQ6) and Compulsion ($\bar{x}$ = SMUQ4, SMUQ7, SMUQ8, SMUQ9). Figure 2 exhibits the Conceptual Model that permeates this study.

Unlike most traditional research in which deductive reasoning precedes the preliminary model – that is then followed by exploratory analysis –, in this study it was only possible to develop the hypothesis after EFA.

Hypothesis

After presenting the scales used, it's possible to formulate the following research hypothesis:

Hypothesis 1a: Withdrawal decreases the effect of Shared Content Anxiety.
Hypothesis 1b: Withdrawal decreases the effect of Privacy Concern Anxiety.
Hypothesis 1c: Withdrawal decreases the effect of Interaction Anxiety.
Hypothesis 1d: Withdrawal decreases the effect of Self-Evaluation Anxiety.
Hypothesis 2a: Compulsion increases the effect of Shared Content Anxiety.
Hypothesis 2b: Compulsion increases the effect of Privacy Concern Anxiety.
Hypothesis 2c: Compulsion increases the effect of Interaction Anxiety.
Hypothesis 2d: Compulsion increases the effect of Self-Evaluation Anxiety.

Confirmatory Factor Analysis

Confirmatory factor analysis (CFA), a covariance-based study (CB-SEM), was conducted to verify the fit of the measurement model with the support of the LISREL v. 8.80 (Jöreskog & Sörbom, 1996) that has specific characteristics in the construction of the model that were not present in the simplified diagram of the theoretical model (Figure 2). Among them, there is a need to indicate the correlations between exogenous variables (in path analysis), as well as the endogenous (dependent) variable receiving an error attribution. To test the convergent and discriminant validity, the strategy of correlating all exogenous and endogenous variables with each other was used. Maximum Likelihood (ML) is the most widely used fitting function for structural equation models and was the method used to estimate the parameters for this study.

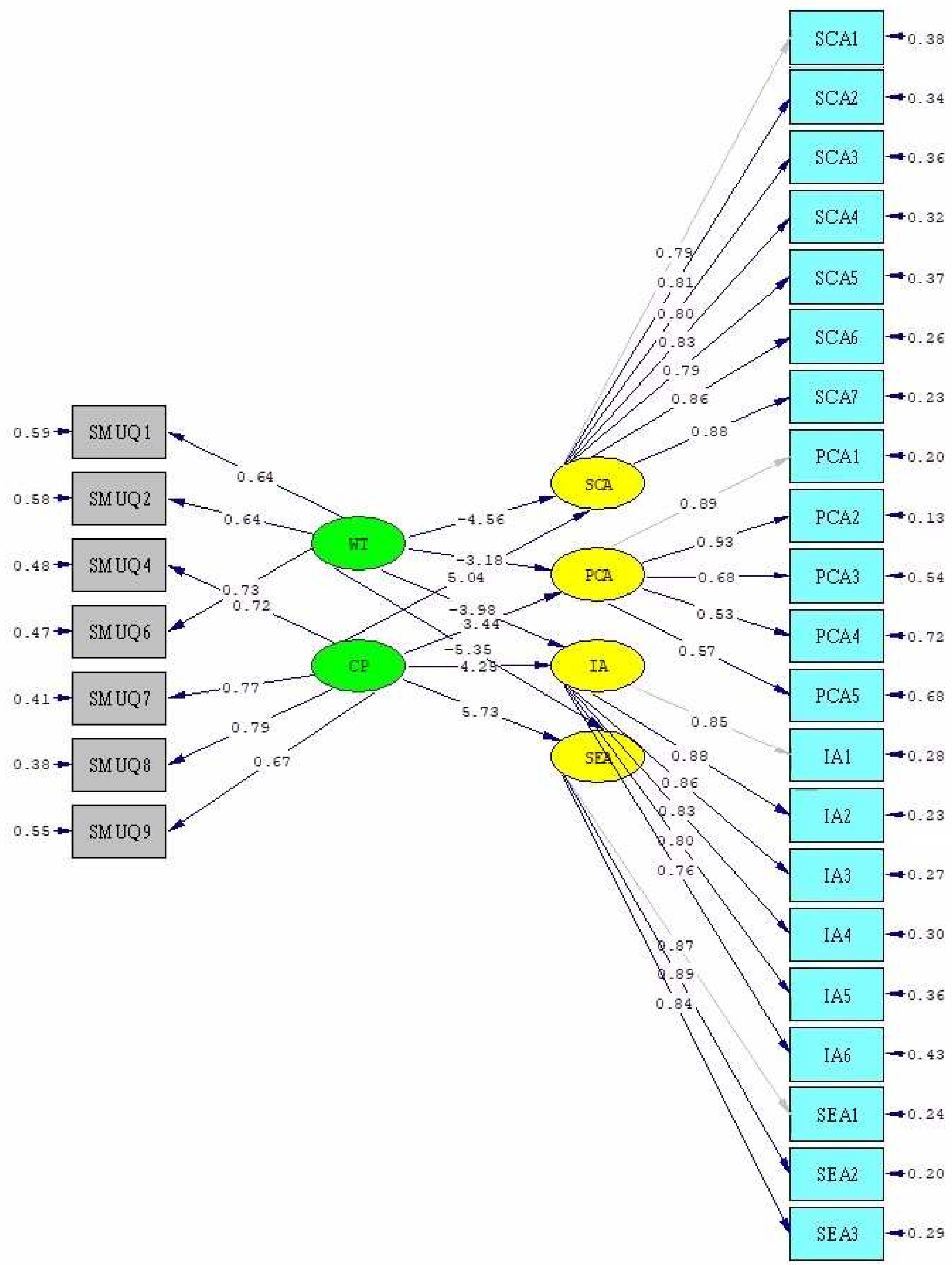

Figure 2 – Final model

The judgment of the fit of the model should reflect the analysis of several criteria. The coefficients considered, the ratio between the chi-square ($\chi 2$) and degrees of freedom (gl), and the CFI, GFI, RMSEA, and SRMR adjustment indexes were used. The $\chi 2$ indicates the magnitude of the discrepancy between the observed and modeled covariance matrix, testing the probability of the theoretical model fitting the data. The higher the value, the worse the adjustment. However, it is more common to consider its reason concerning the degrees of freedom ($\chi 2$/gl) whose values must be between 1 and 3 (Kline, 2015).

The CFI (Comparative Fit Index), GFI (Goodness of Fit of Index), and NFI (Normed Fit Index) indexes calculate the relative adjustment of the observed model, whose values above .95 indicate optimal adjustment and those above .90 indicate adequate adjustment. In turn, the RMSEA (Root of Mean Square Error of Approximation) is also a measure of a discrepancy, with results expected to be less than .05, but acceptable up to .08, despite such a coefficient penalizing complex model. Finally, the SRMR (Standardized Root Mean Square Residual) reports the standardized average of the residues (discrepancies between the observed and modeled matrix), with indexes less than .10 indicative of good fit (Hair *et al.*, 2009; Kline, 2015). For the effectiveness of the analyzes, the maximum likelihood estimator (ML) was used.

The details of the model adjustment are as follows. The value of $\chi 2$=1667.54 and gl=341, resulting in model adjustment ($\chi 2$/gl)=4.89, CFI=.97, GFI=.85 (lower than .90 since this index adjusts for the model's degrees of freedom relative to the number of observed variables and therefore rewards less complex models with fewer parameters), SRMR=.05, and RMSEA=.07, NFI=.96, indicating that all items meet the model and adjustment criteria.

The reliability analysis results, Table 2, are as follows: the value of the AVE (Average Variance Extracted) ranged from .546 to .757, indicating that all variables meet the criteria of >.5 (Bagozzi and Yi, 1988). The internal consistency of CR (Composite Reliability) was considered adequate, ranging from .849 to .936, with all variables above .7 or more (Hair *et al.*, 2009). By the results of the analysis, the measurement model was acceptable and reliable.

Table 2: Convergent and Discriminant Validity Test

Construct	Number of items	AVE	CR	SCA	PCA	IA	SEA	WT	CP
SCA	7	.677	.936	**.823**					
PCA	5	.546	.851	.534***	**.739**				
IA	6	.689	.930	.560***	.456***	**.830**			
SEA	3	.757	.903	.817***	.490***	.662***	**.870**		
WT	3	.652	.849	.351***	.196***	.217***	.262***	**.808**	
CP	4	.610	.862	.497***	.260***	.286***	.424***	.652***	**.781**

Note: *** p-value < .001

Discriminant validity is assessed by examining indicator loadings and correlations between constructs. First, by comparing the square root of the VME of each construct with all the correlations between it and other constructs (Fornell & Larcker, 1981), where the entire square root of the VMEs must be greater than any of the correlations between the corresponding construct and another.

The research brought interesting data that revealed that the measure of fit of the model – the coefficient of determination – for the dependent variables SCA was R^2=.771, PCA was R^2=.323, IA was R^2=.475, and SEA was R^2=.874. Chin (1998) considers that such R^2 values for SCA and SEA are considered high. However, only moderate for IA and low for PCA. Despite being an indicator of quality, the coefficient of determination does not necessarily indicate whether a regressive model is adequate, as it may present a low R^2 value for a good model – in which context must be analyzed (Kvålseth, 1985).

Table 3: Hypothesis confirmation

Paths	Standardized Estimates	Unstandardized Estimates	Standard Error	T Values	Conclusion
H1a: WT → SCA	-4.563	-6.701	1.464	-4.578***	Supported
H1b: WT → PCA	-3.183	-5.709	1.284	-4.448***	Supported
H1c: WT → IA	-3.977	-6.393	1.399	-4.571***	Supported
H1d: WT → SEA	-5.346	-9.222	1.982	-4.653***	Supported
H2a: CP → SCA	5.039	4.944	.972	5.085***	Supported
H2b: CP → PCA	3.435	4.117	.850	4.840***	Supported
H2c: CP → IA	4.249	4.564	.927	4.926***	Supported
H2d: CP → SEA	5.731	6.605	1.313	5.031***	Supported

Note: *** p-value < .001

The proposed research model presented 8 hypothesis in direct relationships, as per Table 3. Of these, all were supported.

The results approve the hypothesis that Withdrawal from using Instagram reduces the effects of all Anxieties (H1a, H1b, H1c, and H1d) considered in this study (SCA, PCA, IA, and SEA). In this sense, less exposure to social media result in lower levels of anxiety. If an individual is withdrawn from sharing content, there is less reason to suffer from Shared Content Anxiety. If they disclose less in social media, lesser will be the perceived privacy risk that could cause Privacy Concern Anxiety. Interaction Anxiety is also reduced when so is that interaction, and the same logic can be applied to Self-Evaluation Anxiety. This is not to exclude the possibility of other types of anxieties arrising from Withdrawal from Instagram use.

Moreover, it was found that PCA is significantly lower than the others, which perhaps can explain or be explained by the fact that most of respondents have their profiles set to public view (n=476; $\bar{x} = 3.03$) and suffer less from PCA ($t_{(755)}$=-4.787; p<.001) than their counterparts with private accounts (n=281; $\bar{x} = 3.42$). The other three constructs showed no medium differences when comparing public and private accounts.

Results also show that Compulsion to use Instagram increases the effects of SCA, PCA, IA, and SEA (H2a, H2b, H2c, and H2d). So by compulsively engaging with social media, sharing content and interacting, individuals are more prone to feelings of such Anxieties. Though many studies have verified how Problematic Social Media Use and social media addiction are related to higher levels of Anxiety (Liu & Ma, 2020; Y.-K. Lee et al., 2014), this research's breakdown into two different constructs (Withdrawal and Compulsion) can bring further insight into how some Anxities are more affected by urge and impulse to use and less by the removal from such addictive use.

CONCLUSIONS

In this section, the conclusions and final considerations will be presented, dealing with the practical and theoretical implications, suggestions for future research and the limitations encountered.

Research Implications

This work aimed to identify the factors and the relationship between Problematic Social Media Use and Anxieties in Instagram Users. It was possible to identify the components of each of the scales under study, analyze the relationship of Instagram functionalities in relation to each effect on mental health, and identify the relationship between factors described in the literature that influence them. The objective was successfully achieved since significant variables were discovered, and relevant information on Instagram use during the COVID-19 pandemic was presented, thus validating the research framework and possible replication it in future studies.

One of the contributions of this study is bringing psychometric scales developed in other areas of study (i.e., Psychology) to bring a level of greater complexity in the interpretative process. Instagram can be understood through various functionality representations due to having an interface representing abstract values related to interactions and points of interest that need some interpretation element. This interpretation's importance is in the search for understanding the purpose of these functions in terms of communication with and about the social world (Schwartz & Mahnke, 2018).

There are certain peculiarities in the case of individuals who manifest mental health effects resulting from Instagram. Individuals with social anxiety, increased loneliness, and problematic social media use can get worse, since these issues affect their daily lives and relationships because of the high frequency of use and extended periods using Instagram. Furthermore, the comparisons they make between their lives and those of other users, and the consequent dependence on the social network, can aggravate the situation. In individuals with social anxiety, Instagram can be a kind of refuge, a safe and comfortable place, far from the judgments and insecurities generated by physical human contact.

In this study, it was found that women use Instagram as much as men, with similar feature adoption, and the highest concentration for both is in the frequency range over two hours a day. A 28.3% of total respondents have been users for more than 8 years, which demonstrates the platform's permanence in users' lives.

Practical Implications

Firstly, this study benefits users of social media, particularly Instagram. Reflecting on how we use the tools and the time available to us, and how it affects our mental health and overall well-being is crucial. Since one's social and psychological circumstances influence media use and effects, being aware of its circumstances provides knowledge to make better decisions and adapt use for a healthier outcome.

Key findings in this study can also benefit Facebook, owner of the Instagram platform, who can better understand its users and further optimize its services and features to diminish adverse mental health effects. By knowing the motivation and the extent of users' experience, Instagram can become a more helpful and cheerful social media.

Other brands and companies with online strategies can take advantage of demographic and usage information provided in this study, as well as learn from consumer behavior exposed by the analysis of the many shopping activities available on Instagram. They can engage with their customers who are social media users to provide support, valuable content, and a better online environment for all.

Finally, this study serves academic purposes and can significantly benefit future endeavors, considering the rarity of individual-focused research in Business studies. It is up to the other institutions to use works such as these to achieve the objectives and show that the academy can actively contribute to market and individual issues.

Limitations and recommendations for future studies

It is understood that the transversal character of the collection method used limits the research, since this approach is based on the analysis of a single moment. Thus, we suggest that future longitudinal tests could advance new discoveries in the field.

Also, due to the restricted sample and mostly obtained for convenience and by judgment, the external validity (Malhotra, 2014), which is the extent to which the results of a study can be generalized, is compromised. Future research could seek to obtain a more representative sample, thus generating results with greater possibility of generalization, so that it is possible to compare different realities between countries.

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APPENDIX

Appendix A: Scales, constructs, items, assertives, factor loading, h² and references

Scale	Constructs/Factors		Item	Assertives	Factor loading	h²	References
Social Anxiety Scale for Social Media Users (SAS-SMU)	Social Anxiety	Shared Content Anxiety	SCA1	On social media... I feel anxious about the fact that others might find my actions awkward.	.817	.668	Alkis et al. (2017)
			SCA2	... I am concerned about being ridiculed by others for the content I have shared.	.849	.720	
			SCA3	... I am concerned about the fact that the content I share will not be liked by others.	.839	.703	
			SCA4	... I am afraid that my close friends will not approve of my behavior.	.860	.740	
			SCA5	... I would feel uncomfortable when my friends publicly express their dislike about content I have shared.	.819	.671	
			SCA6	... I am concerned about disapproval of my behaviors by others.	.872	.760	
			SCA7	... I am concerned about being judged about my shared content by my friends in the presence of others.	.890	.792	
		Privacy Concern Anxiety	PCA1	... the possibility of having my private information acquired by others makes me feel anxious.	.864	.746	
			PCA2	... the possibility of having my private information shared publicly makes me anxious.	.883	.779	
			PCA3	... I feel uneasy when my friends share my private information with people I do not know.	.800	.640	
			PCA4	... I would be concerned if my personal space is accessed without my consent.	.712	.507	
			PCA5	... I feel anxious about how social media companies/executives handle privacy policy regarding my private life.	.710	.504	
		Interaction Anxiety	IA1	... I feel anxious when talking with people I have just met.	.861	.741	
			IA2	... I feel nervous when I talk with people I do not know very well.	.891	.794	
			IA3	... I feel uneasy while making new friends.	.887	.787	
			IA4	... I feel tense when I meet someone for the first time.	.865	.747	
			IA5	... I am afraid of interacting with others.	.847	.717	
			IA6	... I feel nervous when I have to talk with others about myself.	.808	.653	
			SEA1	... I feel anxious about making a negative impression on people.	.914	.835	
			SEA2	... I am concerned about people thinking poorly of me.	.930	.865	

		Self-Evaluation Anxiety	SEA3	...I feel anxious about not being able to meet people's expectations.	.899	.808	
Social Media Use Questionnaire (SMUQ)	Dependence of Use	Withdrawal	SMUQ1	I struggle to stay in places, where I won't be able to access social network sites.	.882	.778	Xanidis and Brignell (2016)
			SMUQ2	I feel angry, when I am not able to access my social network account	.883	.780	
			SMUQ6	I feel anxious, when I am not able to check my social network account	.865	.747	
		Compulsion	SMUQ4	I lose track of time, when using social network sites	.828	.686	
			SMUQ7	I stay online longer than initially intended.	.864	.747	
			SMUQ8	I spend a large proportion of my day using social network sites.	.853	.727	
			SMUQ9	I feel guilty about the time that I spend on social network sites	.817	.667	
			SMUQ3*	My relatives and friends complain that I spend too much time using social network sites.	-	-	
			SMUQ5*	I use social network sites, when I am in the company of friends	-	-	

Note: *items removed in the Exploratory Factor Analysis phase by the extraction method - analysis of the main component.

Source: research data