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# Identifying Factors and the Relationship between Problematic Social Media Use and Anxieties in Instagram Users: A Deep Investigation-based Dual-stage SEM-ANN Analysis

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**Abstract**

This paper aims to identify the factors and the relationship between Problematic Social Media Use (Compulsion and Withdrawal) and Anxieties in Instagram users. The research is descriptive, with a quantitative approach developed through a survey (n=757). After a multi-analytical approach using Covariance-based Structural Equation Modeling (CB-SEM) validated the model, results became inputs to an Artificial Neural Network (ANN) model to predict the Anxieties. Findings pointed out that the most relevant constructs were Shared Content Anxiety and Self Evaluation Anxiety, and the neural network provided empirical evidence to support that Compulsion is the most relevant predictor for Anxieties, increasing its effects. The introduction of this new methodology and the theoretical contribution of the proposed hybrid model opens perspectives of the existing body of knowledge in the literature related to understanding phenomena such as the relationship between Problematic Social Media Use and Anxieties in Instagram users.


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*Keywords:* mental health; social media; Instagram; Structural Equation Modeling, Artificial Neural Network

## 1. Introduction

Social media platforms are one of the most popular and widely used applications on the Internet and have transformed the very nature of communication with rapid expansion and widespread application [1,2]. Additionally,

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there are concerns about the potential detrimental effects of users' social media use (SMU) on their mental health [3–5].

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 behaviours that negatively impact them [6,7].

Social media usage was boosted globally, and 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. It is also important for companies to take into account opportunities and challenges surrounding a better understanding of how their employees can be affected by potential issues related to technology use and managing a healthy psychological life [8].

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 [9,10].

This study considers four dimensions of social anxiety relevant to social media use, as per research by Alkis et al. [9]: 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.

All the aspects raised above bring concerns and motivations that can be summed up to the problem of these research questions addressed in this paper are: RQ1: How does problematic Instagram use affect social anxieties? RQ2: How can the SEM-ANN approach method contribute to understanding the impact of Instagram's use on psychological disturbs?

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 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) [9] and the Social Media Use Questionnaire (SMUQ) [11]. The introduction of this new methodology (a deep investigation-based dual-stage SEM-ANN analysis) and the theoretical contribution of the proposed hybrid model opens perspectives of the existing body of knowledge in the literature related to understanding phenomena such as the relationship between Problematic Social Media Use and Anxieties in Instagram Users.

## 2. Method

### *2.1 Data collection and sample procedures*

This study is classified as empirical exploratory-descriptive, and the research approach adopted was quantitative with a cross-section. The sample is non-probabilistic and was constituted by convenience. 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. For the adaptation of the research instrument and the selected scales to the Brazilian context, we used a back-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 (later integrated to the final sample). The survey was unaltered since no changes were required, and 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 $D^2$ [12]. 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.

*2.2 Data analysis procedures*

Due to the characteristics of the study, descriptive analyzes and three multivariate phases were conducted: a) Exploratory Factor Analysis (EFA) - to identify the components of each of the groups of the scales under study (Social Anxiety and Problematic Social Media Use); b) Covariance-based Structural Equation Modeling (CB-SEM); and c) Artificial Neural Networking. The confirmatory method with CB-SEM based on covariance for a linear approach was done using LISREL v.8.80 software verified the data and tested the structure and hypotheses of the model [13]. CB-SEM is designed for theory building, confirmation, and rejection, alongside rigorous multivariate assumptions. The SEM approach measures the linear interrelationships. At the same time, the Artificial Neural Network (ANN) approach was done using the IBM SPSS v.25 software for both linear and non-linear relationships between the identified factors influencing the variable of interest. Therefore, for the analysis, we employed an integrated approach of SEM-ANN [14–16].

## 3. Data Analysis

*3.1 Profile of respondents*

This section presents the survey respondents' profile to characterize the sample, comprised of 757 people, all Instagram users, considering valid responses. There were 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.

*3.2 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 [12].

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. Subsequently, unidimensionality (score>.50 in the factor) and low cross-load (score<.40 in the other factors) were observed. All variables had adjustments due to commonality (h2<.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 ($\bar{x}_{SCA}$=SCA1, SCA2, SCA3, SCA4, SCA5, SCA6, SCA7), Privacy Concern Anxiety ($\bar{x}_{PCA}$= PCA1, PCA2, PCA3, PCA4, PCA5), Interaction Anxiety ($\bar{x}_{IA}$=IA1, IA2, IA3, IA4, IA5, IA6), Self-Evaluation Anxiety ($\bar{x}_{SEA}$=SEA1, SEA2, SEA3), Withdrawal ($\bar{x}_{SMUQ\_W}$=SMUQ1, SMUQ2, SMUQ6) and Compulsion ($\bar{x}_{SMUQ\_C}$= SMUQ4, SMUQ7, SMUQ8, SMUQ9). Fig 1 exhibits the results of Conceptual Model that permeates this study.

Also, when identifying a structure or ensuring that the measurements reflect the construct correctly, additional EFA can be considered, regardless of the existing theoretical backgrounds. 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 [17].

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.

*3.3 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 that has specific characteristics in the construction of the model that were not present in the simplified diagram of the theoretical model (see Fig 1). 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.

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 [18].

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 [12,18]. 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 [19]. The internal consistency of CR (Composite Reliability) was considered adequate, ranging from .849 to .936, with all variables above .7 or more [12]. 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

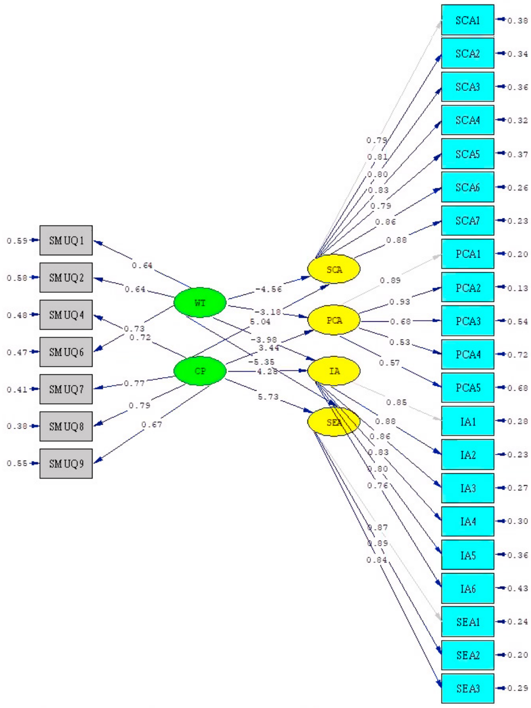


Fig 1. Final model.

Discriminant validity is assessed by examining indicator loadings and correlations between constructs. 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.

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

### *3.4 Artificial Neural Network (ANN)*

Employing a multi-analytical approach, this study combines Structural Equation Modeling (SEM) with neural network analysis. In the first stage the overall research model is tested, and significant hypothesized predictors are determined, and then in the next stage those are used as inputs to the neural network in order to determine the importance of each predictor variable. Artificial Neural Network is one of the most important artificial intelligence techniques – mainly due to its capacity of identifying non-linear relationships – and, by being more robust, can provide higher prediction accuracy when compared to linear models [15,20].

ANN is a computational model that is composed of standard processing units called nodes or neurons (which are analogous to the biological neurons in the brain), used for computing output values from inputs [21]. Every input neuron is given a synaptic weight that is transferred to the hidden layer with hidden neurons to be transformed into an output value by an activation function. The synaptic weights of these connections are then altered via an iterative training process and the knowledge gained from the process is kept for upcoming predictive use [22].

This study performed ANN analysis by using SPSS v.25 software, developed employing a multilayer perceptron training method, with the input layer consisting of 2 independent variables from SEM (Withdrawal and Compulsion) and the output layer consisting of 4 output variables (SCA, PCA, IA, and SEA). To increase effectiveness of training with better performance [15], all inputs and outputs were normalized to the range [0,1]. A ten-fold cross-validation technique was used to avoid overfitting, in which 90% of data was used for network training and the remaining for testing. The Root Mean Square of Error (RMSE) of both data sets for all ten ANNs, as well as their averages and standard deviations, are presented in Table 4 and the ddefinitions of these criteria are given as follows:

$$\mathrm{SSE} = \sum_{t=1}^{n}\left(\mathrm{Q_t} - \widehat{\mathrm{Q}}_t\right) \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\frac{\mathrm{SSE}}{\mathrm{n}}} \tag{2}$$

$\mathrm{Q_t}$ is the observed data (Q) at time t, $\widehat{\mathrm{Q}}_t$ is the predicted value at time t.

Table 4. RSME Values

| | | NN | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | mean | sd |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| SCA | Training | N | 681 | 678 | 672 | 669 | 677 | 682 | 679 | 678 | 678 | 675 | - | - |
| | | SSE | 19.900 | 19.837 | 19.168 | 19.680 | 18.936 | 19.537 | 19.735 | 19.726 | 19.237 | 19.356 | 19.511 | 0.322 |
| | | RMSE | 0.171 | 0.171 | 0.169 | 0.172 | 0.167 | 0.169 | 0.170 | 0.171 | 0.168 | 0.169 | 0.170 | 0.001 |
| | Testing | N | 76 | 79 | 85 | 88 | 80 | 75 | 78 | 79 | 79 | 82 | - | - |
| | | SSE | 1.939 | 1.946 | 2.729 | 2.650 | 2.614 | 1.970 | 2.272 | 2.681 | 2.328 | 2.170 | 2.330 | 0.320 |
| | | RMSE | 0.160 | 0.157 | 0.179 | 0.174 | 0.181 | 0.162 | 0.171 | 0.184 | 0.172 | 0.163 | 0.170 | 0.009 |
| PCA | Training | N | 682 | 669 | 687 | 675 | 697 | 684 | 667 | 694 | 672 | 683 | - | - |
| | | SSE | 23.077 | 22.141 | 23.982 | 22.032 | 23.441 | 22.263 | 22.321 | 22.413 | 22.368 | 22.855 | 22.689 | 0.636 |
| | | RMSE | 0.184 | 0.182 | 0.187 | 0.181 | 0.183 | 0.180 | 0.183 | 0.180 | 0.182 | 0.183 | 0.183 | 0.002 |
| | Testing | N | 75 | 88 | 70 | 82 | 60 | 73 | 90 | 63 | 85 | 74 | - | - |
| | | SSE | 2.114 | 2.753 | 1.881 | 2.829 | 1.919 | 2.700 | 2.508 | 2.393 | 2.826 | 2.216 | 2.414 | 0.366 |
| | | RMSE | 0.168 | 0.177 | 0.164 | 0.186 | 0.179 | 0.192 | 0.167 | 0.195 | 0.182 | 0.173 | 0.178 | 0.011 |
| IA | Training | N | 676 | 682 | 677 | 682 | 680 | 688 | 688 | 673 | 687 | 681 | - | - |
| | | SSE | 23.508 | 24.021 | 23.871 | 23.318 | 23.437 | 24.083 | 23.893 | 23.672 | 23.520 | 23.548 | 23.687 | 0.263 |
| | | RMSE | 0.186 | 0.188 | 0.188 | 0.185 | 0.186 | 0.187 | 0.186 | 0.188 | 0.185 | 0.186 | 0.186 | 0.001 |
| | Testing | N | 81 | 75 | 80 | 75 | 77 | 69 | 69 | 84 | 70 | 76 | - | - |
| | | SSE | 2.542 | 2.132 | 2.819 | 2.782 | 2.633 | 2.624 | 2.134 | 2.674 | 2.513 | 2.496 | 2.535 | 0.237 |
| | | RMSE | 0.177 | 0.169 | 0.188 | 0.193 | 0.185 | 0.195 | 0.176 | 0.178 | 0.189 | 0.181 | 0.183 | 0.008 |
| SEA | Training | N | 694 | 682 | 680 | 684 | 672 | 671 | 683 | 688 | 675 | 677 | - | - |
| | | SSE | 28.000 | 27.489 | 27.733 | 26.707 | 27.260 | 27.365 | 27.900 | 28.720 | 28.112 | 26.819 | 27.611 | 0.612 |
| | | RMSE | 0.201 | 0.201 | 0.202 | 0.198 | 0.201 | 0.202 | 0.202 | 0.204 | 0.204 | 0.199 | 0.201 | 0.002 |
| | Testing | N | 63 | 75 | 77 | 73 | 85 | 86 | 74 | 69 | 82 | 80 | - | - |
| | | SSE | 2.665 | 3.091 | 2.983 | 3.724 | 3.240 | 3.164 | 2.642 | 2.232 | 2.666 | 3.974 | 3.038 | 0.526 |
| | | RMSE | 0.206 | 0.203 | 0.197 | 0.226 | 0.195 | 0.192 | 0.189 | 0.180 | 0.180 | 0.223 | 0.199 | 0.016 |

Table 5. Sensitivity analysis

| | SCA | | PCA | | IA | | SEA | |
|---|---|---|---|---|---|---|---|---|
| Neural network (NN) | WI | CP | WI | CP | WI | CP | WI | CP |
| NN (i) | 0.270 | 0.730 | 0.483 | 0.517 | 0.302 | 0.698 | 0.094 | 0.906 |
| NN (ii) | 0.328 | 0.672 | 0.488 | 0.512 | 0.479 | 0.521 | 0.117 | 0.883 |
| NN (iii) | 0.405 | 0.595 | 0.707 | 0.293 | 0.272 | 0.728 | 0.088 | 0.912 |
| NN (iv) | 0.471 | 0.529 | 0.348 | 0.652 | 0.492 | 0.508 | 0.155 | 0.845 |
| NN (v) | 0.339 | 0.661 | 0.211 | 0.789 | 0.471 | 0.529 | 0.212 | 0.788 |
| NN (vi) | 0.301 | 0.699 | 0.395 | 0.605 | 0.349 | 0.651 | 0.233 | 0.767 |
| NN (vii) | 0.397 | 0.603 | 0.336 | 0.664 | 0.339 | 0.661 | 0.205 | 0.795 |
| NN (viii) | 0.429 | 0.571 | 0.397 | 0.603 | 0.532 | 0.468 | 0.395 | 0.605 |
| NN (ix) | 0.303 | 0.697 | 0.306 | 0.694 | 0.343 | 0.657 | 0.047 | 0.953 |
| NN (x) | 0.328 | 0.672 | 0.432 | 0.568 | 0.416 | 0.584 | 0.210 | 0.790 |
| Average importance | 0.357 | 0.643 | 0.410 | 0.590 | 0.400 | 0.600 | 0.209 | 0.791 |
| Normalized importance (%) | 55.43% | 100% | 71.21% | 100% | 69.49% | 100% | 23.16% | 100% |

Sensitivity analysis was conducted to measure the strength of the weight resistances by calculating the normalized importance of the resistances from the ten ANN simulations. Normalized importance is the ratio of relative importance to greater relative importance and is indicated as a percentage. Table 5 shows that Compulsion is the most significant predictor in the sensitivity analysis, showing 100% normalized importance for SCA ($\bar{x}_{SCA}$=64.3%), PCA ($\bar{x}_{PCA}$=59%), IA ($\bar{x}_{IA}$=60%), and SEA ($\bar{x}_{SEA}$=79%).

## 4. Discussion

We achieved the objective of this research by proposing the development of a hybrid model, in two stages (SEM and ANN), that allows for identifying the determining factors to understanding phenomena such as the relationship between Problematic Social Media Use and Anxieties in Instagram Users.

Instagram users are highly aware of the content shared by them or by others in the platform, and how it also impacts how they view themselves through said content and its given reactions (likes, comments, social comparisons). Alternatively, they are less concerned with privacy issues, and there might be milder influence from anxiety derived from interacting and communicating given the context of only doing so inside social media during the pandemic restrictions.

The proposed research model presented 8 hypotheses 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 [23–25], 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.

The proposed model employed a three-stage SEM-ANN approach – SEM for testing possible relationships and exploring the most significant variables and ANN for predicting the determinants (Compulsion and Withdrawal) for types of Anxiety. Such integrated methodology provides a rigorous and comprehensive reference for the future research work. The neural network provided empirical evidence to support that Compulsion is the most relevant predictor for Anxieties.

As previously mentioned, the benefits and detriments of socia media use can be a matter of how much and how it is used. As an SNS, Instagram enables users to communicate through their profiles, comments, and private messages, as well as showcase their personalities and lives with many other available features. When used in a sustained and frequent manner, and when carefully choosing what types of profile to follow (celebrities, influencers), the negative impacts can be accentuated [26].

The high incidence of use of cosmetic filters in the analysis of Social Anxiety is linked to the fact that making a photo more appealing might increase the likelihood of receiving validation and attention from others. Such like-seeking behavior has similar motivations as trying to minimize negative evaluation from others, a core factor of Social Anxiety. Thus, the use of cosmetic filters will naturally be higher amongst those who are more socially anxious.

Social media remains immensely popular and, as it becomes an increasingly important part of people's life, its impact can have a negative influence in users' mental health regarding Anxiety and Problematic Use, which this study confirms.

## 5. Conclusions

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. Applying two-stage CB-SEM based on deep learning and ANN analysis creates a robust methodological approach, detecting linear and non-linear associations between the constructs.

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. Finally, key findings in this study can also benefit Meta Platforms, Inc., 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.

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