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NOMOFOMO in the health of the Smartphone User for the New Normal: a contribution to the Social Media Health Interaction Theory

NOMOFOMO en la salud del Usuario de Smatphone en la Próxima Normalidad: una contribución a la Teoría de la Interacción de la Salud en las Redes Sociales

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ABSTRACT

Purpose. The paper is aimed to explain how the NOMOFOMO proposal framework, composed of social media innovations acceptance (SMA), *"nomophobia"* (NMF), and *"fear of missing out"* (FOM), interacts with smartphone health user repercussions (HRP), contributing to profile social media health interaction theory (SMT).

Methodology. It is based on a literature review defining a final questionnaire survey to **431** smartphones users (Jun-Aug-2021) with PLS-SEM analysis.

Results. SMA Socialization and Education dimensions, and HRP like pain and movement extremely slowly appearing face like upset or sad, anxiety and anger as central affections.

Originality. The framework gathers four empirically proved separately constructs.

RESUMEN

Propósito. El documento tiene como objetivo explicar cómo el marco de la propuesta NOMOFOMO, compuesto por la aceptación de las innovaciones en las redes sociales (SMA), la *"nomofobia"* (NMF) y el *" miedo a no ser considerdo en la red"* (FOM), interactúan con las repercusiones de los usuarios de salud de los teléfonos inteligentes (HRP), contribuyendo al perfil de la teoría de la interacción de la salud en las redes sociales (SMT).

Metodología. Se basa en una revisión de la literatura que define una encuesta de cuestionario final a 431 usuarios de teléfonos inteligentes (junio-agosto-2021) con análisis PLS-SEM.

Resultados. SMA dimensiones de Socialización y Educación, y PRH como dolor y movimiento de aparición extremadamente lenta cara como malestar o tristeza, ansiedad e ira como afectos centrales.

Originalidad. El marco reúne cuatro constructos empíricamente probados por separado.

1. Introduction

More than 4.80 billion people worldwide use the internet, almost 61% of the world´s total population. With an annual rate of 5.7 % (DAW, 2021) being affected by the COVID-19 pandemic, actual figures may be much higher. Most internet users (92.1 %) use mobile devices to go online at least some time, but computers also account for an important share of internet activity. Mobile devices have become a fixture of everyday life for millions of people. In 2020, the number of unique mobile internet users stood at 4.28 billion, indicating that over 90% of the global internet population uses mobile devices to go online (Statista, 2021a). In fact, after the COVID-19 pandemic the social media innovations acceptance **(SMA)** increased the number of active users being the most popular in Jul-2021 (in millions. Statista 2021b), for instance: Facebook (2,853); Youtube (2,291); WhatsApp (2,000); Instagram (1,386); Facebook Messenger (1,300); WeChat (1,242); Tok-tok (732); QQ (606); Doujin (600); Telegram (550); Kuai Shu (481); Pinterest (478); Reddit (430); Twitter (397); Quora (300).

In Mexico, for instance, 115 million smartphones are using social media as the main reason to use among other different devices like tablets, laptops, or smart TVs, being the most popular social media using: Facebook, WhatsApp, YouTube, Instagram, Twitter, Tok-tok, Telegram, Snapchat, Skype, Pinterest, Tinder and LinkedIn (AIMX, 2021).

Unfortunately, after the prolonged COVID-19 pandemic lockdown during 2020, two symptoms or syndromes considered as problematic digital media use in mental health have emerged with the assumption of have been reinforced: the *"nomophobia"* (NOM) and the *"fear of missing out"* (FOM). Both syndromes are still out and do not appear in the current Diagnostic and Statistical Manual of Mental Disorders (DSM-A), Fifth Edition (APA, 2013). Nowadays, there is not exist a social media health interaction theory (SMT) that fulfills the requirements here described. Therefore, we introduced the NOMOFOMO-HRP framework that involves the social media innovations acceptance (SMA), *"nomophobia"* (NMF), and *"fear of missing out"* (FOM) to undertake an analysis of how they are interacting on smartphone health user repercussions (HRP).

1.1.The Social Media Health Interaction Theory (SMT)

Social influences are a primary factor in the adoption of health behaviors; there are important studies and advances in our understanding of how social networks influence the collective dynamics of health behavior (Centola, 2013). Research has shown that social media influences can affect collective health outcomes ranging from epidemic obesity to smoking behaviors, which have important consequences both for theoretical models of social epidemiology and for the practical design of interventions and treatment strategies (Luke & Harris, 2007).

Very few platforms in our lives affect us more than social media for communication. This is since mediated messages and images surround us, providing us with information and entertainment and ways to connect with others for several purposes like getting an education, doing our job, or doing business (West and Turner 2018). However, despite all the advantages explained above, there is a lack of an integral theory describing how the intensive interaction with SMA affects smartphone users' health. In this context, there are very few works now, about description of a SMT like Ramos (2017) describing a framework that explain:

> *"What stable social media interactions legitimatize particular thoughts and practices regarding issues such as health and illness and help to transform individuals through effective transfer of knowledge through social media*."

This framework involves four underlying assumptions: 1. Social media is a means of accessing and gaining information; 2. Social media creates a virtual community where interaction occurs; 3. Different groups may have diverse cultural practices regarding the acquisition and dissemination of information and 4. People who engage in interaction are rationally seeking to maximize their health. Our contribution is based on this framework.

1.2.The Social Media Innovations Acceptance (SMA)

During the last years, the technology based on social media has been a notorious rise, and massive spread and usage (El-Hadadeh et al., 2012). Several social media sites (e.g., Twitter, Facebook, LinkedIn) have employed dynamic social contexts in which online communities can be made and continued easily by facilitating communications and social connections among smartphone users. Such networking opportunities help make groups, communities, and people with shared interests remain more associated (Gupta & Bashir, 2018). The total number of active smartphones users and social communities has increased 9.6% in only nine months (Jul-2020 to Apr-2021). For such platforms to be accepted by smartphones users, several questions are posed: how do they keep the social media audience engaged? what content is appropriate for the new normal environment? The innovative social media platforms should evolve from promotional and entertainment channels to collaborative social media channels for users (Wright, 2021).

For such reasons, we have decided to use the Gupta & Bashir (2018) framework studies previously implemented on 420 university students, describing the smartphone user profile that implies items on several dimensions, such as *"socialization"* (items SMA1, SMA2), *"education"* (items SMA3, SMA4), *"job issues"* (items SMA5, SMA6), *"informativeness or how to get news"* (items SMA7, SMA8), *"entertainment"* (items SMA9, SMA10), and *"sell-buy business activities*" (items SMA11, SMA12).See **Table 2**.

Unfortunately, there is evidence that the social media innovations influence the mental health of smartphone users, especially in students (Rajesh & Priya, 2020), provoking depression, anxiety, and psychological distress mainly in adolescents with a prevalence increased by 70% in the past 25 years in young people before the **COVID-19** pandemic times (Keles et al., 2019). Furthermore, the growing psychological morbidity in young people was not known conclusively before 2020 (*Ibídem*).

1.2. Nomophobia (NOM).

The term, an abbreviation for *"no-mobile-phone phobia,"* was coined during a 2008 study by the UK Post Office who commissioned YouGov (a British international Internet-based market research and data analytics firm), a UK-based research organization, to evaluate anxieties suffered by mobile phone users. The first works about psychological factors involved in the overuse of a mobile phone were started from Bianchi & Philips (2005). They described symptoms as low self-esteem (when individuals looking for reassurance use the mobile phone in inappropriate ways) and extroverted personality (when naturally social individuals use the mobile phone to excess). It is possible that nomophobia symptoms may be caused by other underlying and preexisting mental disorders, with likely candidates including social phobia or social anxiety disorder, social anxiety (King et al., 2013) and panic disorder (King et al., 2010). In this context we have several works that have tried to propose solid constructs to determine the main factors of this problematic digital media use in mental health, for instance in the last five years, such as Dasgupta (et al., 2017), Lee (et al., 2018), Daei (et al., 2019), Majeur (et al., 2020), Lin (et al., 2021); these studies were based on Yildrim & Correia (2015) nomophobia questionnaire. According to SCOPUS (Sep-2021), published papers with word: *"nomophobia"* has been increased in the last 10 years, for instance: 2012 (1); 2013 (2); 2014 (3); 20015 (2); 2016 (4); 2017 (20); 2018 (21); 2019 (29); 2020 (54); 2021 (49). In our case, we selected the framework of Yildrim & Correia (2015), composed by four factors with 12 items adapted to the Mexican smartphone users', involving several dimensions such as *"not being able to access information"* (items NMF1, NMF2. NMF3 is included by Mejía-Trejo, 2019 about the use of Apps); the *"giving up convenience"* dimension (items NMF4, NMF5, NMF6, NMF7, NMF8); *"not being able to communicate"* (items NMF9, NMF10) and *"loss off connection"* dimension (items NMF11, NMF12). See **Table 2**.

Hence, we proposed the following hypothesis:

H1: "SMA *contributes to generating more* NMF."

1.3.The Fear of Missing Out (FOM)

Social media utilities have made it easier than ever to know about the range of online or offline social activities one could be engaging in as a duality. For instance, the variety of social media resources provide a broad interaction opportunity; on the other side, more options than can be pursued produce practical restrictions and limited time. The *"fear of missing out"* (FOMO, here FOM) is a social anxiety caused by worries that others may have more satisfying lives than themselves (Dossey, 2014). The JWT (2012) report defines it as:

> "*It is the uneasy and sometimes all-consuming feeling that you're missing out—that your peers are doing, in the know about or in possession of more or something better than you"*

It is characterized by a desire to stay continually connected with what others are doing. It is defined as a pervasive apprehension that others might be behaving rewarding experiences from which one is absent (Przybylski et al., 2013). According to SCOPUS (Sep-2021), published papers with word: *"fomo"* has been increased in the last 10 years, for instance: 2012 (1); 2013 (2); 2014 (1); 2015 (5); 2016 (13); 2017 (15); 2018 (35); 2019 (52); 2020 (83); 2021 (79).

Some works have tried to measure it, for instance in the last five years, the work of Ragusa (2017), Syahniar (et al., 2018), Can & Satici (2019), Kim (et al., 2020), Tandon (et al., 2021). These works are based on a previous study of Przybylski (et al., 2013) supported thoroughly on three studies (one to operationalize the construct, study 2 aimed to determine a nationally representative cohort of how demographic, motivational, and well-being factors relate to FOM and study 3 to examine the behavioral and emotional correlations to FOM) to get a framework composed by only ten items (FOM1 to FOM10). See **Table 2**.

Therefore, we proposed the following hypothesis:

H2: *"*SMA *contributes to generating more* FOM.*"*

H3: "FOM *contributes to generating more* NMF."

1.4.The Smartphone Health User Repercussions (HRP)

As far as all there are a few studies that have tried to explain the NOM and FOM relationship; for instance, and according to SCOPUS (Sep-2021), published papers with the words: *"nomophobia and fomo"* have only appeared since 2017: 2017 (1); 2018 (1); 2019 (4); 2020 (3); 2021 (2). Some works have tried to measure it, such as Kuss & Griffiths (2017), Gezgin (et al., 2018); Gezgin (et al., 2019), Shiva (et al., 2020), Yilmaz and Bekaroglu (2021) but not based on the health of a smartphone user after a prolonged COVID-19 pandemic lockdown like this study offers.

By another hand, to get a measurement of how NOMOFOMO is related to smartphone health user repercussions (HRP), we proposed to use the PROMIS (Patient-Reported Outcomes Measurement Information System ®) predictors. PROMIS (2021) is a set of person-centered measures that evaluate and monitor adults' and children's physical, mental, and social health. It can be used with the general population and with individuals living with chronic conditions. Here are proposed 9 items as HRP predictors describing anger (HRP1), anxiety (HRP2), depression (HRP3), excessive fatigue (HRP4), two pains (Pain1 and Pain2): pain with extremely slowly and appearance in individuals' faces as upset or sad (HRP5), pain that interferes the social and household activities (HRP6), inability to exercise hard (HRP7), with two satisfactions (Satisfaction1 and Satisfaction2), satisfaction on abilities to perform the daily routines in work (HRP8), and finally, with satisfaction on abilities to do leisure activities (HRP9). See **Table 2**.

In this form, we proposed the following hypotheses:

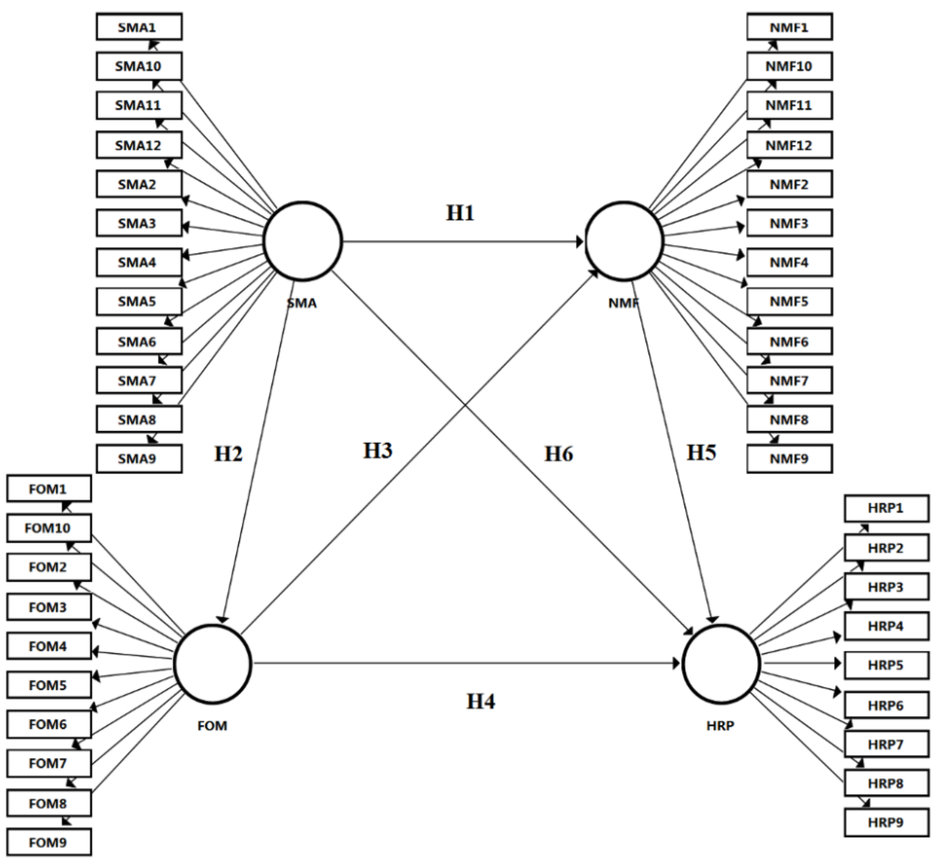
H4: *"*FOM *contributes to generating more* HRP*."*

H5: *"*NMF *contributes to generating more* HRP*."*

H6: "SMA *contributes to generating more* HRP."

See **Figure 1.**

Figure 1. The NOMOFOMO-HRP Framework proposal



Notes:
Social Media Innovations Acceptance (SMA); Nomophobia (NMF); Fear of Missing Out (FOM); Smartphone Health User Repercussions (HRP)

Source: Own

2. Designing the final NOMOFOMO-HRP framework

Because we considered that the items are interchangeable, we posed reflective specification since they (hypothetically) represent the construct equally (as against related to the formative constructs, when dropping an indicator may change the meaning of that construct) (Hair et al., 2019b).

Finally, **Table 2** shows how are displayed 43 indicators that describe the **3** factors of the NOMOFOMO construct related to the smartphone health user repercussions (HRP) as fourth construct and the authors that support them.

3. Methodology

It is designed in **5** steps, described as follows:

Stage 1. It was based on a literature review to determine state of the art about NOMOFOMO -HRP framework and SMT. This is in terms of the social media innovations acceptance (SMA) interact with *"nomophobia"* (NMF) and *"fear of missing out"* (FOM) determining the smartphone health user repercussions (HRP) level as the main constructs, considering the consequences of the prolonged emergency closure due to the COVID-19 pandemic. The final framework is composed by the social media innovations acceptance (SMA) factor described with 12 indicators, the nomophobia (NOM) factor based on 12 items, the *"fear of missing out"* (FOM) with 10 indicators and finally, the smartphone health user repercussions (HRP) containing 9 descriptors. All the framework totalizes 43 indicators. See **Table 2**.

Stage 2. The survey data was applied to 431 smartphone users (Jul-Aug-2021) according to age, gender, marital status, education, monthly income (Mexican pesos), (see Table 1), and the period considered as the next normal times (period after COVID-19 pandemic in Mexico).

Stage 3. We contribute with an entire solid empirical reflective framework proposal analyzed with Partial Leased Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 3.3.3 software. This PLS-SEM determines the outer loading and tests the framework's reliability with convergent and discriminant validities (see **Tables 2 and 3**). Here, only one combination of underlying factors and indicators (items) are obtained according to their outer loading obtained through the NOMOFOMO framework on the smartphone health user repercussions (HRP).

Stage 4. Once the outer loadings prove and test the framework's reliability with convergent and discriminant validities, the datasets are analyzed to explain the interrelated factors and indicators to determine the structural measurement model and the hypotheses tests. This is helpful to assess the NOMOFOMO construct explanatory capabilities on the smartphone health user repercussions (HRP) (see **Table 4**).

Stage 5. Results analyses, discussion, and conclusions.

3.1.Demographic data

According to the results obtained from the frequency analysis of 431 Mexican consumers (Jun-Aug-2021), the most important data of the participants were: 306/18-29 years old (71%); 260 females and 171 males (60.3% /39.7%), 353 singles (81.9%), 313 college students (72.6%), 283 with monthly income less than 9,000 Mexican pesos (65.7%).

About the social media use, we had social media to become more sociable: WhatsApp (256/59.4%); social media used to get news of the world through the smartphone: Facebook (200/46.4%); social media used to get education through the smartphone: YouTube (265/61.5%);

social media used to do the job through the smartphone: WhatsApp (286/66.4%); social media used to get entertainment through the smartphone: Tik-Tok (126/29.2%); social media used to sell-buy through the smartphone: Facebook (259/60%).

Participants were invited to answer the questionnaire via e-mail google forms (see **Table 2),** explaining the scope to encourage them and collect their opinions. Participation was voluntary, confidential; no rewards were provided. Therefore, the sample is considered representative of smartphone users in Mexico. See **Table 1.**

Table 1. Research sample demographic profile

Measure	Items	Frequency	Percentage (%)
Age	<18	22	5.1
	18-29	**306**	**71**
	30-39	38	8.8
	40-49	24	5.6
	50-59	16	3.7
	60-69	21	4.9
	>70	4	0.9
	Total	431	100
Gender	**Female**	**260**	**60.3**
	Male	171	39.7

	Total	431	100
Marital Status	Single	**353**	**81.9**
	Married	66	15.3
	Divorced	9	2.1
	Widow	3	0.7
	Total	**431**	**100**
Education Level	Middle-School	3	0.7
	High-School	64	14.8
	College	**313**	**72.6**
	Master	36	8.4
	Doctor	15	3.5
	Total	**431**	**100**
Monthly Income (pesos)	**< =10000**	**283**	**65.7**
	10000-15000	45	10.4
	15000-20000	45	10.4
	20000-25000	21	4.9
	25000-30000	10	2.3
	30000-35000	14	3.2
	35000-40000	4	0.9
	40000-45000	4	0.9
	>45000	5	1.2
Social Media to become more sociable	Facebook	67	15.5
	Twitter	6	1.4
	Instagram	97	22.5
	WhatsApp	**256**	**59.4**
	LinkedIn	0	0
	YouTube	3	0.7
	Tik-Tok	2	0.5
	Total	431	100
Social Media that I use to get education through my smartphone	Facebook	41	9.5
	Twitter	33	7.7
	Instagram	25	5.8
	WhatsApp	33	7.7
	LinkedIn	20	4.6
	YouTube	**265**	**61.5**
	Tik-Tok	14	3.2
	Total	431	100
Social Media that I use to do my job through my smartphone	Facebook	48	11.1
	Twitter	6	1.4
	Instagram	34	7.9
	WhatsApp	**286**	**66.4**
	LinkedIn	23	5.3
	YouTube	31	7.2
	Tik-Tok	3	0.7
	Total	431	100
Social Media that I use to get news of the world through my smartphone	**Facebook**	**200**	**46.4**
	Twitter	119	27.6
	Instagram	32	7.4
	WhatsApp	12	2.8
	LinkedIn	4	0.9
	YouTube	52	12.1
	Tik-Tok	12	2.8
	Total	431	100
	Facebook	89	20.6

Social Media that I use to get entertainment through my smartphone	Twitter	6	1.4
	Instagram	106	24.6
	WhatsApp	9	2.1
	LinkedIn	6	1.4
	YouTube	89	20.6
	Tik-Tok	**126**	**29.2**
	Total	431	100
Social Media that I use to sell-buy through my smartphone	**Facebook**	**259**	**60**
	Twitter	0	0
	Instagram	98	22.7
	WhatsApp	68	15.8
	LinkedIn	1	0.2
	YouTube	5	1.2
	Tik-Tok	0	0
	Total	431	100

Source: Own

3.2.Sampling

The critical discussion of applications sample size technique involves how large a sample is needed to produce reliable results. Although PLS-SEM is not affected by the sample size (Kock & Hadaya, 2018), here we adopt the basic criterion of covariance-based structural equation modeling (CB-SEM), the rule of thumb for sample size (Hair et al., 2019a). This is 10 times the number of arrows pointing at a construct, whether a formative indicator or a structural path to an endogenous construct. In our case 43 indicators x 10 times= 430. The 431 Mexican smartphone users' sample (Jun-Aug-2021) fulfill this condition widely.

3.3.PLS-SEM analysis technique

PLS-SEM is a component-based approach estimation differing from the CB-SEM to structural equation modeling. PLS-SEM fits a composite model, maximizing the variance explained on how this goal might be accomplished. The PLS-SEM is composed of the *"measurement model"* representing the observed data and the underlying factor relationships, and *the "structural model"* showings the relationships between the underlying factors (Henseler et al., 2012; Hair et al., 2017a). The *"structural equation"* model is solved by an iterative algorithm estimating the underlying factors through *"measurement model"* and *"structural model"* in alternating steps or partial. The *"measurement model"* calculates the underlying factors as a weighted sum of its manifest factors. Through simple or multiple linear regression between the underlying factors estimated by the *"measurement model"* is how the *"structural model"* computes the underlying factors. Until convergence is achieved, this algorithm repeats itself. PLS-SEM analyzes, explores, and tests the established and underlying conceptual models and theory being preferable over CB-SEM when it is unknown whether the data's nature is a common factor or composite-based (Henseler et al., 2012; Hair et al., 2017a).

4. Results.

We have reflective constructs (mode A) (Hair et al., 2017b) into the framework that are assessed, as follows:

4.1. The measurement model internal consistency reliability, significance, and variance assessment as convergent validity

They were computed according to SmartPLS 3.3.3 software, with values per factor, of Cronbach´s alpha (>=0.7) (Hair et al., 2017a), of rho_A index (>=0.7) (Dijkstra & Hanseler, 2015a), of composite reliability index (CRI) (>=0.7), and average extracted variance index (AVE) (>=0.5) (Hair et al., 2017a). For internal consistency reliability, Cronbach's alpha is referred as the lower bound being the composite reliability the upper bound. The indicator's outer loadings should be > 0.70. The indicators between 0.40-0.70 as outer loadings are for removal only such action leads to an increase in composite reliability and AVE above the suggested threshold value (Hair et al., 2017a). Convergent validity is measured AVE, which is the grand mean value of the squared loadings of the indicators associated with the construct (Fornell & Larcker, 1981).

Therefore, we had to remove FOM2 due to the problems with collinearity; SMA5 and SMA8 to SMA 12, HRP8 and HRP9 to adjust AVE and the measurement model achieving all the indexes mentioned above. Hence, the framework fulfills the reliability and convergence validity required. See **Table 2.**

Table 2. The NOMOFOMO-HRP measurement model internal consistency reliability, significance, and variance assessment as convergent validity.

Factor: Social Media Innovations Acceptance (SMA) Cronbach's alpha (>=0.7): **0.821**; Dijkstra–Henseler's rho (>=0.7): **0.828**; CRI (>=0.7): **0.868**; AVE>0.5: **0.522**				**Outer Loadings (p-value)**	**Author**
No.	**Dimension**	**Item**	**Indicators**		
1	Socialization	**SMA1**	I use social media to become more sociable through my smartphone.	0.733 (0.000)	Gupta & Bashir (2018)
2		**SMA2**	I use social media to attending social gathering through my smartphone.	0.750 (0.000)	

3	Education	**SMA3**	I use social media for collaborative learning through my smartphone.	0.693 (0.000)	
4		**SMA4**	I use social media for online academic group discussion through my smartphone.	0.766 (0.000)	
5	Job Issues	**SMA5**	I use social media to do better my job through my smartphone.	Removed. Problems with AVE and the measurement model	
6		**SMA6**	I use social media to improve my curricular aspect through my smartphone.	0.692 (0.000)	
7	Informativeness	**SMA7**	I use social media as a source of news because they are more credible through my smartphone.	0.699 (0.000)	
8		**SMA8**	I use social media because it is easy to search and find any kind of information through my smartphone.	Removed. Problems with AVE and the measurement model	
9	Entertainment	**SMA9**	I use social media to get relief my stress through my smartphone.		
10		**SMA10**	I use social media for watching pictures, movies, and videos, through my smartphone.		
11	Business Activities	**SMA11**	I use social media to search opportunities to sell-buy products/services through my smartphone		
12		**SMA12**	I use social media because it is easy to do business through my smartphone.		
Factor: Nomophobia (NMF) Cronbach's alpha (>=0.7): **0.928**; Dijkstra–Henseler's rho (>=0.7): **0.934;** CRI (>=0.7):**0.938**; AVE (>=05): **0.556**				**Outer Loading (p-value)**	**Author**
No.	**Dimension**	**Item**	**Indicators**		
13	*Not being able to access information*	**NMF1**	I would feel uncomfortable without constant access to information through my smartphone.	0.717 (0.000)	Yildrim & Correia (2015)
14		**NMF2**	I would be annoyed if I could not look information up on my smartphone when I wanted to do so.	0.700 (0.000)	
15		**NMF3**	I would be annoyed if I could not use my social media Apps on my smartphone when I wanted to do so.	0.757 (0.000)	Mejía-Trejo (2019)
16	*Giving up convenience*	**NMF4**	Running out of battery in my smartphone would scare me.	0.764 (0.000)	Yildrim & Correia (2015)
17		**NMF5**	If I were to run out of smartphone credits or hit my monthly data limit, I would panic.	0.713 (0.000)	
18		**NMF6**	If I did not have a data signal or could not connect to Wi-Fi, then I would constantly check to see if I had a signal or could find a Wi-Fi network.	0.768 (0.000)	
19		**NMF7**	If I could not use my smartphone, I would be afraid of getting stranded somewhere.	0.706 (0.000)	
20		**NMF8**	If I could not check my smartphone for a while, I would feel a desire to check it.	0.806 (0.000)	
21	*Not being able to communicate*	**NMF9**	I would feel anxious because I could not instantly communicate with my family and/or friends.	0.731 (0.000)	
22		**NMF10**	I would be worried because my family and/or friends could not reach me.	0.681 (0.000)	
23	*Loss off connection*	**NMF11**	I would be nervous because I would be disconnected from my online identity.	0.797 (0.000)	
24		**NMF12**	I would be uncomfortable because I could not stay up-to-date with social media and online networks.	0.799 (0.000)	
Factor: Fear of Missing Out (FOM)				**Outer**	**Author**

Cronbach's alpha (>=0.7): **0.903**; Dijkstra–Henseler's rho (>=0.7): **0.907**; CRI (>=0.7): **0.922**; AVE (>=0.5): **0.570**			**Loading (p-value)**	
No.	**Item**	**Indicators**		
25	**FOM1**	I fear others have more rewarding experiences than me when I noticed through my smartphone.	0.820 (0.000)	Przybyiski (et al., 2013)
26	**FOM2**	I fear my friends have more rewarding experiences than me when I noticed through my smartphone.	Removed. Problems with collinearity	
27	**FOM3**	I get worried when I find out my friends are having fun without me when I noticed through my smartphone.	0.853 (0.000)	
28	**FOM4**	I get anxious when I don´t know why my friends are up to when I noticed through my smartphone.	0.856 (0.000)	
29	**FOM5**	It is important that I understand my friend in "jokes" when I noticed through my smartphone.	0.731 (0.000)	
30	**FOM6**	Sometimes, I wonder if I spend too much keeping up with what is going on when I use my smartphone.	0.617 (0.000)	
31	**FOM7**	It bothers me when I miss an opportunity to meet up with my friends when I use my smartphone.	0.788 (0.000)	
32	**FOM8**	When I have a good time it is important for me to share the details online (e.g., updating status) using my smartphone.	0.716 (0.000)	
33	**FOM9**	When I miss out on a planned get-together through my smartphone, it bothers me	0.639 (0.000)	
34	**FOM10**	When I go on vacation, I continue to keep tabs on what my friends are doing using my smartphone.	0.734 (0.000)	

Factor: Health User Repercussion (HRP) Cronbach's alpha (>=0.7): **0.888**; Dijkstra–Henseler's rho (>=0.7): **0.900**; CRI (>=0.7): **0.913**; AVE (>=0.5): **0.602**				**Outer Loading (p-value)**	**Author**
No.	**Dimension**	**Item**	**Indicators** *"In the past 7 days…"*		
35	Anger	**HRP1**	I felt angry.	0.789 (0.000)	PROMIS (2021)
36	Anxiety	**HRP2**	I felt anxiety.	0.824 (0.000)	
37	Depression	**HRP3**	I felt depressed.	0.789 (0.000)	
38	Excessive Fatigue	**HRP4**	I feel excessive fatigue.	0.788 (0.000)	
39	Pain1	**HRP5**	I was in pain. I moved extremely slowly appearing my face like upset or sad	0.841 (0.000)	
40	Pain2	**HRP6**	I was in pain that interfered my daily social and household activities.	0.771 (0.000)	
41	Inhability	**HRP7**	I am not able to exercise hard like running, swimming, etc.	0.604 (0.000)	
42	Satisfaction1	**HRP8**	I am satisfied with my ability to perform my daily routines and my work.	Removed. Problems with AVE	
43	Satisfaction2	**HRP9**	I am satisfied with my ability to do leisure activities.		

Notes:

- **CRI.** Composite Reliability Index. Values 0-1.
- **rho_A.** Values between 0.6-0.7 are acceptable in exploratory research, 0.7-0.9 reflect satisfactory to good results (Hair et al., 2019a). Values >0.95 suggest that the indicators could be measuring the same phenomenon and they are semantically redundant (Hair et al., 2019a; Drolet & Morrison, 2001) with a potential common bias, this is, the variation is from the instrument not by respondents (Straub et al., 2004).
- **AVE**. Average Variance Extracted Index. >0.5 suggests that more than 50% of the construct represents the items variance (Fornell & Larcker, 1981).
- Indicators are according to Likert Scale 1-7: using Likert Scale 1-7 (1. Strongly disagree; 2. Disagree; 3. Somewhat disagree; 4. Neither agree or disagree; 5. Somewhat agree; 6. Agree; 7. Strongly agree). This type of

scale provides a balance between the respondents' complexity and the ease of analysis of the information (Hair et al., 2019a).
Source: Own adaptation and using SmartPLS 3.3.3. software

4.2. The NOMOFOMO measurement model discriminant validity

It was computed with SmartPLS 3.3.3 software. It points to if an underlying factor is measuring a different construct and the degree to which indicators show an example of the target construct. It was calculated according to the traditional discriminant validity assessment method, which requires all relationships between constructs to be less than the lowest of the AVE's square root values. (Fornell & Larcker, 1981). See **Table 3.**

Table 3. NOMOFOMO-HRP measurement model discriminant validity

Fornell-Larcker Criteria (Diagonal= Root Square -AVE-) for discriminant validity				
Factors	**FOM**	**HRP**	**NMF**	**SMA**
FOM	**0.755**	-	-	-
HRP	0.479	**0.776**	-	-
NMF	0.661	0.428	**0.746**	-
SMA	0.427	0.256	0.437	**0.723**
HTMT Ratio<= 0.85<=0.90 for convergent validity				
Factors	**FOM**	**HRP**	**NMF**	**SMA**
FOM	-	-	-	-
HRP	0.526	-	-	-
NMF	0.706	0.454	-	-
SMA	0.465	0.274	0.459	-

Note:
HTMT. It ensures that different constructs capture different concepts. The cut-off value is 0.90 if the constructs are conceptually similar); a more conservative cut-off value is 0.85 (Henseler, et al., 2015). Bootstrapping ensures that HTMT results are statistically significantly different from 1.0 because cut-off values have a high likelihood of falsely rejecting discriminant validity and are very conservative (i.e., Type II error) (Franke & Sarstedt, 2019)
Source: Own using SmartPLS 3.3.3 software

It includes the heterotrait-monotrait **(**HTMT) of the relationship criterion as a complement to evaluate discriminant validity. An estimate of what the true correlation between two constructs would be if they were perfectly measured is represented through the HTMT approach is (i.e., when they are perfectly reliable HTMT <=0.85<=0.90) (Henseler et al., 2015; Hair et al., 2017a). Hence, the framework fulfills the discriminant validity.

4.3.The significance of the structural model relationships.

Path coefficients are the hypothesized relationship among the constructs. They are ranged in standardized values between −1 and 1 (strongly negative or strongly positive). Values close to 0 are weak relationships. The *p*-values and the *f2* effect sizes dictate the significance of path coefficients used on bootstrapping. It produces a sample distribution approaching the normal distribution; the result is used to establish critical t-*values* (Hair et al., 2017b), and subsequently the *p*-values to discuss the clinical or practical significance (Kraemer et al., 2003).

Besides, to modify research conclusions, practical significance involves the magnitude of the observed effect and if it is enough. Therefore, a statistically significant relationship may not be practically significant. Also, some path coefficients might be very small effect size but significant; hence, they are essential to draw appropriate conclusions. There is no consensus, so judgments on the practical significance rely on experts' considerations about measuring practical significance (Kraemer et al., 2003). In this way, the significance of the structural model relationships is proved according to the hypotheses following **Figure 2.**

4.4.NOMOFOMO-HRP Model´s explanatory power

The coefficient of determination explained variance, or R^2 value, is an essential critical measure in PLS-SEM because it measures the model's explanatory power. By each endogenous construct, R^2 measures the proportion of variance explained. In our case, the factor HRP with an R^2 of 0.252 (see **Table 4**) means that 25.2% of HRP variation, is explained by all the constructs that point to HRP. Threshold values are not provided because they depend on the model's complexity and the subject matter. Thereby, adjusted R^2 criterion, is a good practice to consider because it adjusts the R^2value based on the model size (James et al., 2013). A specific exogenous underlying factor can be assessed if it has a substantial impact on the endogenous ones, using the f^2 effect size (Cohen, 1988). It measures if the exogenous construct has a substantial impact on the endogenous one. Thresholds values: <0.02 represents no effect; 0.02–0.15 for small effect size; 0.15-0.35 for a medium-sized effect;>0.35 a large effect size was proposed by Cohen (1988).

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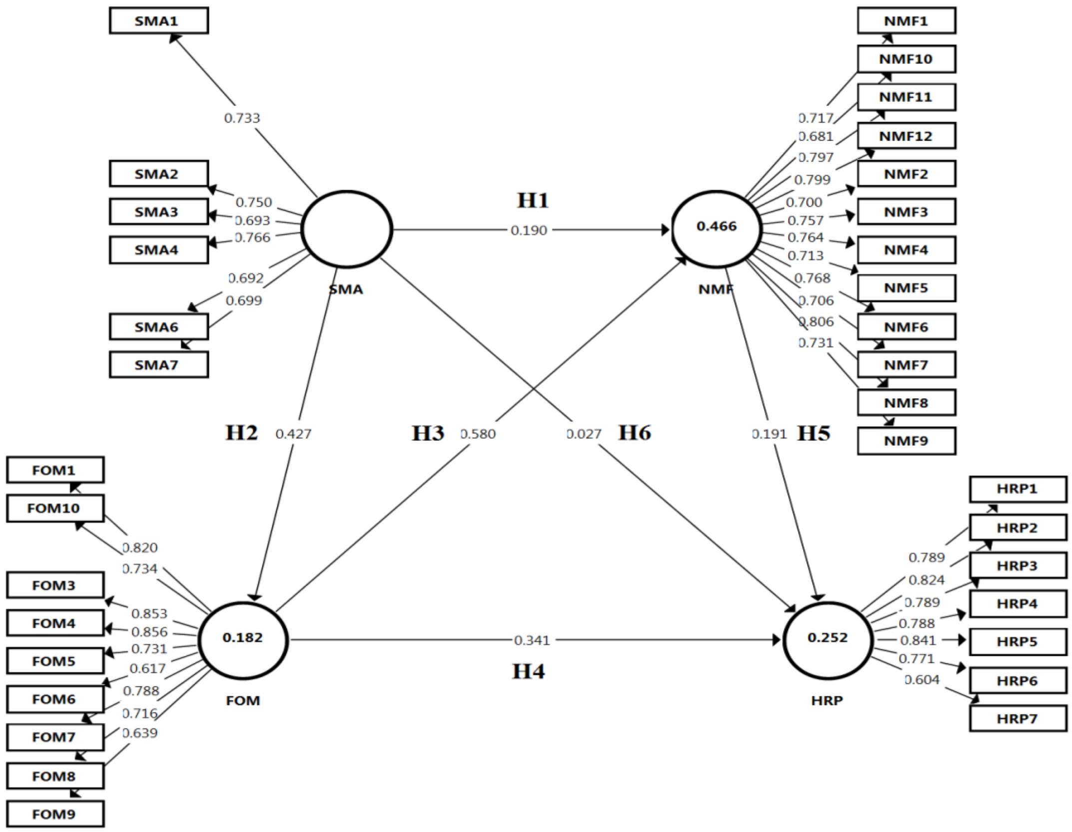
Figure 2. NOMOFOMO-HRP path coefficients, coefficient of determination (R^2) and hypotheses tests



Source: Own using SmartPLS 3.3.3 software

Therefore, the framework fulfills the required conditions except for the model fit (SRMR, dULS, dG). In this case, the framework cannot confirm the results, only to explain them. (Hair et al., 2017a, Hanseler et al., 2015). See **Table 4.**

Table 4. NOMOFOMO-HRP Structural Measurement Model and Hypotheses tests

Hypotheses	Paths	Path (t-value; p-value)	Result Approved Rejected/	5%-95% confidence interval	Interval Result (Crossing 0?)	f^2 Effect Size (0.02<=0.15<=0.35)
H1: "SMA contributes to generating more **NMF"**	**SMA → NMF**	0.190 [3.671; 0.000]	Approved	[0.105, 0.271]	No	**0.437**
H2: "SMA *contributes to generating more* **FOM"**	**SMA → FOM**	0.427 [11.770; 0.000]	Approved	[0.370, 0.487]	No	**0.427**
H3: *"***FOM** *contributes to generating more* **NMF***"*	**FOM → NMF**	0.580 [13.993; 0.000]	Approved	[0.514, 0.647]	No	**0.580**

H4: *"**FOM** contributes to generating more **HRP**"*	**FOM → HRP**	0.341 [5.086; 0.000]	Approved	[0.089, 0.292]	No	**0.452**
H5: *"**NMF** contributes to generating more **HRP**"*	**NMF → HRP**	0.191 [3.040; 0.000]	Approved	[0.417, 0.585]	No	**0.191**
H6: *"**SMA** contributes positively on **HRP**"*	**SMA → HRP**	0.027 [0.569; 0.285]	**Rejected**	[-0.055, 0.103]	**Yes**	**0.256**
Endogenous Factor	**Adjusted R^2**	**Model Fit**	**Value**	**HI99**		
FOM	0.180	SRMR	NA	NA		
HRP	0.247	dULS	NA	NA		
NMF	0.467	dG	NA	NA		

Notes:

- **NA**. Not Applicable
- One-tailed t-values and p-values in parentheses; bootstrapping 95% confidence intervals (based on n= 5000 subsamples) SRMR: standardized root mean squared residual; dULS: unweighted least squares discrepancy; dG: geodesic discrepancy; HI99: bootstrap-based 99% percentiles.
- f^2 **.** Effect size**.** 0.02, 0.15, and 0.35 are interpreted as small, medium, and large (Hair et al. 2017a)
- R^2 . Coefficients of determination represent the amount of explained variance of the endogenous constructs in the structural model. Therefore, values of 0.25, 0.50, 0.75 for target constructs are considered as weak, medium, and substantial, respectively (Hair et al. 2017a)
- **SRMR.** The Standardized Root Mean Square Residual is a common fit measure for CB-SEM (Henseler et al., 2015). For misspecification of PLS-SEM models detection is also used (Henseler et al., 2014). Besides, it is included the following fit measures: squared Euclidean distance (dULS) and the geodesic distance (dG) (Dijkstra & Henseler, 2015b)

Source: Own using SmartPLS 3.3.3 software

5. Discussion

Nowadays, mobile technology based on laptops, tablets, and smartphones presents incredible comforts and opportunities. At the same time, this facilitates accomplishing tasks with generalized popularity in the present for society (Bartwal & Nath, 2019) thanks to their communicative power and people's engagement with those devices (Prasad et al., 2017). As a result of the COVID-19 pandemic times, 2020 thus far has seen an unprecedented year of mobile growth. According to Briskman (2020), mobile downloads and revenue in Q2 both spiked more than one-third compared to the same quarter last year, netting 33.2 billion installs and more than USD 14.5 billion in total consumer spend (excluding the Chinese app market). It seems that mobile is the new normal (Hokenson, 2020). Therefore, mobile technology has become an integral part of human activities in the first part of the XXI century, producing important behavioral changes in human habits and actions (King et al., 2010; Bragazzi et al., 2019).

Nonetheless, since the first decade of this century, there is evidence about behavioral syndromes, mainly in the use of smartphones that has noticeably increased (Lin et al., 2017) and characterized as highly addictive, antisocial, and dangerous phenomena (Pivetta et al., 2019). Therefore, it must be considered a public health issue due to the excessive and massive use of smartphones (Basu et al., 2018; Aboujaoude, 2019). These devices produce high dependence on the users (Tams et al., 2018) and pathologies that are recognized until now, such as the *"nomophobia"* and the *"fear of missing out,"* that they are necessary to be included in the Diagnostic and Statistical Manual of Mental Disorders (APA, 2013).

5.1.Theoretical implications

To achieve all the mentioned above, it requires the confirmation of a body of knowledge based on literature review about the social media interaction theory (SMT) proposed by Ramos (2017). In the first instance, the SMT could establish parameters to analyze the consequences on human behavior, the use of mobile devices, and the services associated with them. This paper aims to highlight the importance of the SMT design with the introduction of the NOMOFOMO-HRP framework. This framework is based on three proved constructs, like Gupta & Bashir (2018) as social media innovations acceptance (SMA), *"nomophobia"* (NOM) by Przybyiski (2013), and *"fear of missing out"* (FOM) proposed by Yildrim and Correia (2015) (2015). The framework describes how to interact NOMOFOMO with a well-recognized scale that measures and report several mental disorders as smartphone health user repercussions (HRP). In this sense, it is included mental disorders like anger, anxiety, depression, fatigue, excessive fatigue, pain with extremely slowly and appearing in individuals face as upset or sad, pain that interferes the social and household activities, inability to exercise hard, with satisfaction on abilities to perform the daily routines in work, and finally, with satisfaction on abilities to do leisure activities. All of them are described in PROMIS (2021) (Patient-Reported Outcomes Measurement Information System®).

5.1.1. The PLS-SEM NOMOFOMO-HRP measurement model

Based on PLS-SEM with SmartPLS 3.3.3. software, Table 2 results show that the NOMOFOMO-HRP measurement model internal consistency reliability, significance, and variance assessment as convergent validity are fitted into the parameters required for each indicator. Such of parameters required were Cronbach's alpha (>=0.7); Dijkstra–Henseler's rho (>=0.7); CRI (>=0.7); AVE (>=0.5); outer loading (>=0.7) and p values (<=0.05).

However, some items were removed due to problems with:

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a. Collinearity in factor *"fear of missing out"* **(**FOM), in the items: FOM2 (*"I fear my friends have more rewarding experiences than me when I noticed through my smartphone."*). This item was very similar to answer for the respondent's perception with (FOM1) *"I fear others have more rewarding experiences than me when I noticed through my smartphone."* This situation apparently evolves the perception of "*others"* and *"friends"* as one conglomerate as *"friends";* a suggestion is to analyze this kind of perception as a consequence of the long lockdown by COVID-19 pandemic (Brito, 2021; Thomas, 2021).

b. AVE to assure the convergent value's index required in:

1. For factor social media innovations acceptance (SMA), in the items:

SMA5 (*"I use social media to do better my job better through my smartphone."*) of "*job issues"* dimension; SMA8 (*"I use social media because it is easy to search and find any kind of information through my smartphone."*) of *"informativeness"* dimension*;* SMA9 (*"I use social media to get relief my stress through my smartphone."*); SMA10 ("*I use social media for watching pictures, movies, and videos, through my smartphone."*) of *"entertainment"* dimension; SMA11 (*"I use social media to search opportunities to sell-buy products/services through my smartphone"*) and SMA12 *("I use social media because it is easy to do business through my smartphone."*) of the *"business activities"* dimension.

2. For factor smartphone health user repercussions (HRP**),** in the item:

HRP8 (*"I am satisfied with my ability to perform my daily routines and my work."*) of *"satisfaction1"* dimension and HRP9 (*"I am satisfied with my ability to do leisure activities."*) of *"satisfaction2" dimension.*

On the **NOMOFOMO-HRP** framework, it is necessary to design the improvement of the result of items with an outer loading of 0.40 – 0.70 and (p-value <0.05) to be more descriptive. It may be to make the data from demographic groups more proportional, decreasing the bias or adapting better the items around the cultural values, especially all in the range of outer loading >0.6<0.7 before being removed (Hair et al. 2017a). If dropping the item that loads poorly increases the AVE significantly (or from an unacceptable level to an acceptable level, i.e., >0.50), it should be discarded (ibidem), being in this case (see **Table 2**):

The suppression of items SMA5, SMA8, SMA9, SMA10, SMA11, SMA12, HRP8, and HRP9 obeys to the fact of the kind of the respondents almost mainly youngers 71% (18-29 years old), 60.3% females, 81.9% singles, 72.6% college students with 65.7% monthly income less than 9,000

Mexican pesos, surely still supported by family income. The evidence shows that kind of demographic sample is very susceptible to the effects of NOM and FOM concerning social and education dimensions related to HRP.

Indeed, following **Table 2** we have the subsequent findings more relevant according to loading factor/p value. These are SMA4 0.766 (0.000), (*"I use social media for online academic group discussion through my smartphone."*) followed by SMA2 0.750 (0.000), *("I use social media to attending social gathering through my smartphone."*) being the next SMA1 0.733 (0.000), (*"I use social media to become more sociable through my smartphone."*) with SMA7 0.699 (0.000), (*"I use social media as a source of news because they are more credible through my smartphone."*) after SMA3 0.693 (0.000), (*"I use social media for collaborative learning through my smartphone."*) and finally, SMA6 0.692 (0.000) (*"I use social media to improve my curricular aspect through my smartphone.*").

These dimensions are evident, closely, and understandable if we consider that our sample based on students are interested in encouraging their studies and socialization due to the impact of social distancing on social connection and well-being through the influence of smartphone use (David & Roberts, 2021). Radical change in the way content is produced and consumed, and interactions occur in online spaces where most youngers socialize, learn, and communicate during the unprecedented lockdown due to the COVID-19 pandemic (Tejedor et al. 2020).

About *"nomophobia"* (NMF), no item was removed being the most relevant items according to loading factor/p value, NMF8 0.806 (0.000), ("*If I could not check my smartphone for a while, I would feel a desire to check it."*); NMF12 0.799 (0.000) (*"I would be uncomfortable because I could not stay up-to-date with social media and online networks."*); NMF11 0.797 (0.000) (*"I would be nervous because I would be disconnected from my online identity.*"); NMF6 0.768 (0.000) (*"If I did not have a data signal or could not connect to Wi-Fi, then I would constantly check to see if I had a signal or could find a Wi-Fi network."*) followed by NMF4 0.764 (0.000), (*"Running out of battery in my smartphone would scare me."*); NMF3 0.757 (0.000); (*"I would be annoyed if I could not use my social media Apps on my smartphone when I wanted to do so."*); NMF9 0.731 (0.000), *("I would feel anxious because I could not instantly communicate with my family and/or friends."*; NMF1 0.717 (0.000), *("I would feel uncomfortable without constant access to information through my smartphone.*"); NMF5 0.713 (0.000), (*"If I were to run out of smartphone credits or hit my monthly data limit, I would panic."* NMF7 0.706 (0.000), (*"If I could not use my*

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smartphone, I would be afraid of getting stranded somewhere."; NMF2 0.700 (0.000), (*"I would be annoyed if I could not look information up on my smartphone when I wanted to do so."*) NMF10 0.681 (0.000)., (*"I would be worried because my family and/or friends could not reach me."*).

The dimensions involved in the order of importance by the users fear to be threatened are *"giving up convenience"* (NMF8, NMF6, NMF4, NMF5, NMF7), *"loss of connection"* (NMF12, NMF11), *"not being able to communicate"* (NMF9, NMF10) *"not being able to access information*" (NMF3, NMF1, NMF2).

These results confirm the source of chronic anxiety, discomfort, even pain that the users suffer. People having *"nomophobia"* can be identified by certain characteristics such as *'never switching off the phone," "repeatedly checking for missed texts and calls," "taking their phone everywhere," "indulging in it at inappropriate times,"* and *"deliberately missing face-to-face interaction.'* In some severe cases, *"nomophobics"* may also face physical side effects such as *"panic attacks," "shortness of breath," "trembling," "sweating", "accelerated heart rate," "pain in the hand joints, neck, and back pain," etc.* when their phone connection dies or is otherwise unusable (Kaur et al., 2021; Kanmani et al. 2017).

If we analyze the construct *"fear of missing out"* (FOM) the most relevant items according to loading factor/p value (excluding FOM2), are FOM1 0.820 (0.000), (*"I fear others have more rewarding experiences than me when I noticed through my smartphone."*) FOM4 0.856 (0.000), (*"I get anxious when I don´t know why my friends are up to when I noticed through my smartphone."*); FOM3 0.853 (0.000), (*"I get worried when I find out my friends are having fun without me when I noticed through my smartphone."*) FOM7 0.788 (0.000), (*"It bothers me when I miss an opportunity to meet up with my friends when I use my smartphone."*) FOM10 0.734 (0.000), (*"When I go on vacation, I continue to keep tabs on what my friends are doing using my smartphone."*); FOM5 0.731 (0.000), (*"It is important that I understand my friend in "jokes" when I noticed through my smartphone."*) FOM8 0.716 (0.000). (*"When I have a good time it is important for me to share the details online (e.g., updating status) using my smartphone."* FOM9 0.639 (0.000), (*"When I miss out on a planned get-together through my smartphone, it bothers me."*) ; FOM6 0.617 (0.000), (*"Sometimes, I wonder if I spend too much keeping up with what is going on when I use my smartphone."*).

These results confirm the main profile of the FOM, a pervasive apprehension that others might be having rewarding experiences from which one is absent (Kim et al., 2020a). FOMO-driven

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consumption is proposed to affect consumption experience for being grounded on extrinsic than intrinsic rewards (Kim et al. 2020b). It can become problematic, leading to anxiety, interrupted sleep, lack of concentration and dependence on social media to generate gratification or a reward (Alutaybi et al. 2020). The results show that individuals reporting high levels of FOMO (FOM) and by consequence, they are more likely to want to stay constantly connected with others and are, therefore, more likely to engage with social media and technology (Przybylski et al., 2013).

Finally, about smartphone health user repercussions (HRP), we have the most relevant items according to loading factor/p value are HRP5 0.841 (0.000), "(*I was in pain. I moved extremely slowly appearing my face like upset or sad."*); HRP2 0.824 (0.000), (*"I felt anxiety".*); HRP1 (*"I felt anger"*) and HRP3 0.789 (.000) (*"I felt depressed"*); HRP4 0.788 (0.000) (*"I feel excessive fatigue"*); HRP6 0.771(0.000),(*"I was in pain that interfered my daily social and household activities."*), and HRP7 0.604 (0.000), (*"I am not able to exercise hard like running, swimming, etc. "*).

The findings of this study are aligned with previous research about how *"nomophobia"* (NOM) and *"fear of missing out"* (FOM). Together produce a serial of physical and mental affections in the social media user, such as depression, neck pain, visual impairment, obesity, carpal tunnel syndrome, behavior disorders, hopelessness, insecurity, alexithymia, lack of tolerance, social isolation, low self-esteem, decreased physical and social activities, sleep disorder and energy lowness, in/out-vehicle traffic accidents and low academic performance (Hosgor & Hosgor, 2019). These kinds of phobias are a type of anxiety. They provoke a significant fear response when the individual thinks of what he is afraid of, often causing emotional and physical symptoms. Existing information about *"nomophobia"* (NOM) and *"fear of missing out"* (FOM) suggests it occurs more frequently in teenagers and young adults; a fact proved here (Raypole, 2019).

5.1.2. The PLS-SEM NOMOFOMO-HRP structural model

Here is discussed all the hypotheses posed, according to **Table 4**, as follows:

At the respect of the H1: *"*SMA *contributes to generating more* NMF*"* and H2: "SMA *contributes to generating more* FOM" both are considered as high f^2 effect size (Hair et al., 2017a) and hence, approved. Therefore, the SMA-NMF relationship is high due to the SMA (Gupta & Bashir, 2018) dimensions of *"socialization"* and *"education"* producing *"nomophobia"* (NMF) (Yildrim & Correia, 2015). On the other hand, the SMA-FOM relationship is high due to the SMA (Gupta &

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Bashir 2018) dimensions of *"socialization"* and *"education"* producing *"fear of missing out"* (FOM) (Przybyiski et al., 2013) on the social media users of the sample.

About H3: "FOM *contributes to generating more* NMF" and H4: "FOM *contributes to generating more* HRP" both are considered as high f^2 effect size (Hair et al., 2017a) and hence, approved. Therefore, the FOM-NMF relationship is high due to the FOM (Przybyiski et al., 2013) on (NMF) (Yildrim & Correia, 2015). On the other hand, the FOM-HRP is high due to the FOM (Przybyiski et al., 2013) on HRP (PRISM, 2021).

In the case of H5: "NMF *contributes to generating more* HRP" and H6: "SMA *contributes positively on* HRP" both are considered as medium f^2 effect size (Hair et al., 2017a). However, H5 is accepted, and H6 is rejected, proving that it is not the fact only to accept the use of social SMA (Gupta & Bashir 2018) but also the mediation of factors such as NOM or FOM to provoke HRP (PROMIS, 2021). Besides, we hope that NOMOFOMO-HRP framework and its results contribute to make the body of knowledge necessary to conform the social media health interaction theory (SMT).

5.2. Practical implications

The incidence rate of *"nomophobia"* (NOM) and *"fear of missing out"* (FOM) disorders were high on the smartphone health user repercussions (HRP) and almost null between social media innovations acceptance (SMA) and HRP**.** The pain and movement extremely slowly appearing face like upset or sad, the anxiety and anger were the three most representative affections to the demographic majority sample in this study, youngers between 18-29 years old (**71%** of the respondents) in the dimension's *"socialization"* and *"education."* Therefore, the study's findings have important implications for public policymakers, government mental health in first instance to design plans against the consequences of such mental disorders on the demographic subject under study, in our case university students between 18-29 years old.

The NOMOFOMO-HRP practical implications could describe the different affections treated in several protocols more detailed in PROMIS (2021). For instance, if the 9 items of the current HRP were interchanged for all the recognized set of scales of person-centered measures that evaluates and monitors physical, mental, and social health in adults and children contained in PROMIS (2021) or other National Institutes of Health.

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NOMOFOMO-HRP framework and its results could contribute to describing the effects of *"nomophobia"* and *"fear of missing out"* with more detail to help in the inclusion of such mental diseases in the new edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5**,** APA, 2013). Mental health experts have not yet decided on formal diagnostic criteria for these conditions, and even more, after a prolonged lockdown such as of COVID-19 pandemic.

6. Limitations and future studies

All empirical studies have certain limitations:

First. Sampling methods may limit survey results due to recruiting respondents' *"snowball self-report"* nature. The survey results are based on the questionnaire's self-reported data to remind them of their opinions.

Second. NOMOFOMO-HRP framework could be proved with several demographic category data like people of different generations (age), gender, education, marital status, monthly income, etc., under several different mental (anxiety, stress, depression, etc.) several physical (slowly, pain, hard movements) and different social roles (people on retirement, active in their jobs, household activities or leisure activities) associated to different levels of satisfaction. This could prove different NOMOFOMO-HRP since chronic diseases or pandemic scenarios (Mejía-Trejo, 2021a). Different scenarios could be used to verify what specific kind of HRP are presented. Suppose these data are extracted from a specific public and disease as data to be precisely collected, categorized, and assessed to refine a final NOMOFOMO-HRP for control disease.

Third. It is suggested the application of fuzzy set Qualitative Comparative Analysis (fsQCA) (Ragin, 2008; Mejía-Trejo, 2021b) to the final NOMOFOMO-HRP framework. This action serves to verify how many different patterns of the underlying factors would be obtained (or not) to the same result about a health care tool against chronic and pandemic diseases, besides the unique results obtained from PLS-SEM.

7. Conclusions

In times of severe chronic or pandemic diseases is essential to take advantage of specific characteristics of the smartphone users like our study 431 smartphone Mexican users' respondents (Jun-Aug-2021), being 306/18-29 years old (71%); 260 females and 171 males (60.3% /39.7%), 353 singles (81.9%), 313 college students (72.6%), 283 with monthly income less than 9,000 Mexican pesos (65.7%). This demographic data was the basis for the empirical proof of the NOMOFOMO-HRP framework with 43 items and 4 proved factors.

The NOMOFOMO-HRP is a potential tool of analysis that allows broadening the scope of how the social media innovations acceptance (SMA), *"nomophobia"* (NOM), and *"fear* of missing out*"* (FOM) are interacting to smartphone health user repercussions (HRP). The health environments analyzed with PLS-SEM were physical, mental, and social. Therefore, we conclude:

First. The main social media innovations acceptance (SMA) affected by *"nomophobia"* (NOM) and *"fear of missing out"* were placed in the dimensions of: *"socialization"* and *"education"* . The SMA-HRP relationship is almost null.

Second. The main smartphone health user repercussions (HRP) to be attended were the pain and movement extremely slowly appearing face like upset or sad, the anxiety and anger.

Third. The NOMOFOMO-HRP framework could be refined with other disease health protocols if the items of HRP are interchanged to be more detailed further mental, physical, social studies and help in the inclusion of such mental diseases in the new edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5, APA, 2013)

Fourth. NOMOFOMO-HRP hopes to be a contribution to social media health interaction theory (SMT).

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