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The smartphone addiction degree estimation scale: Enhancing assessment and understanding of gender differences in youth

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ABSTRACT

Current psychometric instruments for assessing smartphone addiction often fail to account adequately for age and gender differences, largely due to their reliance on traditional factor analytic approaches. This study employs a sequential application of Factor Analysis and Item Response Theory to develop a brief smartphone addiction scale for individuals aged 18–25 that can be flexibly applied according to the severity of addiction exhibited by the individual.

The original 42-item questionnaire was administered to a sample of 1994 European university students. Results supported a three-factor structure consistent with core components of substance addiction: Tolerance/Control Deficit, Withdrawal Syndrome, and Negative Consequences. A fourth factor related to physical and health consequences was successfully integrated into the Negative Consequences factor without compromising model fit or reliability.

The incorporation of Item Response Theory enhanced measurement precision by transforming the instrument into an adaptive test capable of estimating smartphone addiction severity based on individual response patterns. The final scale retained 20 of the original 42 items while maintaining strong psychometric properties. Application of the scale to the analysis of gender differences in smartphone addiction demonstrated that substantive conclusions vary depending on the analytical framework employed, helping to explain inconsistencies reported in the existing literature.

Gender-specific analyses indicated that men were more likely to report productivity loss and reduced social opportunities, whereas women more frequently endorsed smartphone use as a strategy for coping with negative

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[1] You were the first to embark on this journey, and your untimely passing has left a void that cannot be filled. Your presence is profoundly missed, and your memory remains with us in every step of this work.

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emotional states. Overall, the proposed Smartphone Addiction Degree Estimation Scale (*SADES*) shows strong potential as a reliable tool for epidemiological research and for informing public health interventions targeting problematic smartphone use.

1. Introduction

Smartphones have become ubiquitous personal devices, offering constant Internet access and delivering immediate gratification ranging from social interaction and information seeking to entertainment and stress relief. Beyond their functional utility, these devices also serve as salient markers of identity and social status (Bian & Leung, 2015; Panova & Lleras, 2016; Primack et al., 2017; Skierkowski & Wood, 2012). However, this ubiquity is a double-edged sword. Persuasive design architectures and the hyper-accessibility of mobile content may undermine user self-regulation, fostering impulsive and dysregulated usage patterns (Allcott et al., 2022; Chen, Hedman, Distler, & Koenig, 2023; Flayelle et al., 2023; Lehdonvirta, 2022; Montag et al., 2019).

Consequently, Problematic Smartphone Use (PSU), often operationalized in the literature as smartphone addiction, has emerged as a critical area of inquiry. PSU is generally defined as excessive smartphone-related behavior characterized by difficulty disengaging despite potential adverse physical, psychological, or social consequences (Busch & McCarthy, 2021). The implications of PSU are profound and multifaceted. Empirical research indicates that PSU is associated with impairments in core cognitive processes, including attention, memory, reflective functioning (Bhargava & Velasquez, 2021; Williams, 2018) and also negative association with physical activity (Meng et al., 2025; Yu et al., 2025) and interpersonal communication, especially in females (Qiu et al., 2025). These impairments extend to interpersonal communication, academic performance, and overall well-being (Asao et al., 2024; Kushlev & Dunn, 2019; Skowronek et al., 2023; Zhao et al., 2024). Additionally, clinical associations have been reported between PSU and musculoskeletal pain, sleep disturbances, and symptoms of depression (Aljomaa et al., 2016; Bian & Leung, 2015; Billieux et al., 2015; Busch & McCarthy, 2021; Dong et al., 2024; Han et al., 2024; Jain et al., 2025; Leow et al., 2023; Luk et al., 2018; Meng et al., 2024; Mohamed et al., 2023; Sihoe et al., 2023; van Deursen et al., 2015; Wang et al., 2025; Winkler et al., 2020; Yu et al., 2025).

This issue appears particularly pronounced among university populations. Epidemiological studies report high but markedly variable prevalence rates of PSU among students, ranging from 17.9% (Mok et al., 2014) and 29.8% (Chen, Liu, et al., 2017) to 38.4% (Kurtaran, 2024), 39.8% (Demirci et al., 2015), 44.6% (Hawi & Samaha, 2016), 52.7% (Erdoganoglu & Arslan, 2019), 54.3% (Lai et al., 2025), and as high as 65.8% (Telgote et al., 2021). Such variability underscores not only contextual and cultural differences but also persistent challenges in measurement that highlight the need for improved methods.

A central limitation in PSU research concerns instrumentation. Early measures, including the Mobile Phone Problem Use Scale (MPPUS; Bianchi & Phillips, 2005), its adolescent adaptation (MPPUS-10; Foerster, Roser, Schoeni, & Röösli, 2015), the Problematic Mobile Phone Use Questionnaire (PMPUQ; Billieux et al., 2008), and the Questionnaire on Experiences Related to Mobile Phones (CERM; Beranuy et al., 2009), were developed before the widespread diffusion of smartphones with constant high-speed Internet access. Although more recent instruments, such as the Smartphone Addiction Scale (SAS; Kwon, Lee, et al., 2013), the Problematic Use of Mobile Phones Scale (PUMP; Merlo et al., 2013) and the Smartphone Application-Based Addiction Scale (SABAS; Csibi et al., 2018), better reflect contemporary usage patterns, they largely rely on traditional factor-analytic approaches that may lack the precision required to differentiate severity levels accurately.

These measurement limitations lead to unclear results regarding gender differences in smartphone (SP) addiction. The existing literature presents inconsistent findings. Some studies report higher levels of problematic use among female students (Bagci & Peksen, 2018; Kwon et al., 2013a,b), often attributed to greater engagement with social and communicative SP functions (Billieux et al., 2007; Demirci et al., 2021; Takao et al., 2009). Other studies report higher risk among male students (Aljomaa et al., 2016; Öztunç, 2013), suggesting that differences in usage motivations, particularly gaming-related activities, may play a role. A third body of research reports no significant gender-based differences in PSU (Alotaibi et al., 2022; Bouna-Pyrrou et al., 2015; Chen et al., 2017; Laconi et al., 2017; Okasha et al., 2021; Spilková et al., 2017; van den Eijnden et al., 2018). These inconsistencies may reflect, at least in part, limitations in measurement and construct validity. In this context, IRT's capacity to support measurement invariance offers a robust strategy for disentangling genuine behavioral differences from methodological artifacts.

To address these issues and resolve such inconsistencies, there is a need for psychometric tools that capture the shared behavioral mechanisms underlying addictive SP use, including loss of control, withdrawal-like experiences, and functional impairment, with greater precision across severity levels. Therefore, the present study integrates Confirmatory Factor Analysis (CFA) with Item Response Theory (IRT). This combined approach offers a complementary perspective not systematically incorporated into existing PSU instruments. CFA evaluates the factorial structure and the relationships between items and the underlying latent construct, whereas IRT calibrates individual items by their discrimination capacity and severity thresholds, enabling differentiation across levels of problematic use. By integrating CFA and IRT, this approach enhances measurement precision by identifying items that optimally assess PSU across the full severity continuum, allowing to build an adaptive test. This, in turn, enables the development of a shorter, more informative, and more efficient instrument without compromising construct validity. Moreover, IRT addresses item-level properties such as severity and discrimination, thereby reducing measurement error and improving robustness. Such parsimony is particularly valuable in large-scale epidemiological studies and applied clinical contexts, where assessment burden must be minimized.

Consequently, the main goal of this study is to develop and validate a psychometrically robust instrument for assessing PSU among individuals aged 18–25, integrating Confirmatory Factor Analysis and Item Response Theory within a single measurement framework. By combining these approaches, the study provides a precise, efficient, and reliable tool suitable for both large-scale research and applied clinical contexts, while minimizing assessment burden. A secondary goal is to apply this instrument to examine gender-related patterns in PSU symptomatology, offering a methodologically grounded interpretation of inconsistent findings in the literature. More broadly, the study illustrates how conclusions about PSU may vary across measurement strategies and analytical models, thereby contributing to a clearer, more coherent understanding of prior evidence.

The article is structured as follows: after describing the data collection process, items, and participants, the results of the CFA model in the first phase are presented. In the second phase, the conclusions from the CFA are complemented and extended using the IRT approach. Finally, the study offers evidence of the instrument's construct validity through an examination of gender differences in SP addiction, highlighting how methodological approaches can influence conclusions, potentially explaining inconsistencies in the existing literature, and delineating implications for future research.

2. Method

2.1. Participants and procedure

Data were collected from 2019 students enrolled in social and behavioral science faculties and technical schools at universities from different regions within Spain (Andalusia, Basque Country, Catalonia, Madrid) and from the Veneto region (Italy), between June 2022 and November 2024. Inclusion criteria required participants to be at least 18 years old, enrolled at the university, and attend a classroom-based SP intervention in which the objectives of the study were explained to them so that they would voluntarily agree to take part. The final sample comprised 1994 individuals, excluding cases with excessive missing data or inconsistent responses to similarly worded items, which indicated a lack of engagement.

Of the participants, 65.2% self-identified as women, 34.1% as men, and 0.7% as non-binary or preferred not to disclose their gender. The higher proportion of women reflects the actual gender distribution in the student populations in most non-technical degree programs in Europe. The participants ranged from 18 to 25 years of age, with an average of 20.7 years (SD = 1.96). Specifically, in Spain, the Statistics on University Students (2025) show that in the most represented degrees in our sample, women accounted for 78.5% in Education; 65.2% in Social Sciences and Journalism; 55.1% in Administration and Law; and 73.2% in Health and Social Services."

Participants were fully informed regarding the purpose of the study, and explicit informed consent was obtained before proceeding. No incentives were provided. Before completing the questionnaire, which they accessed via a link on their laptop or SP, participants were informed of their rights, confidentiality, anonymity, and the treatment of their data, guaranteed during and after participation. The study complied with the ethical standards set out in the Declaration of Helsinki (World Medical Association, 2013).[2]

2.2. Measurement scale development

First, based on a literature review of SP addiction measurement scales published between 2004 and 2022, 198 items were selected focusing on a wide range of aspects. Iterative rounds of expert consultation (involving specialists in addiction, clinical psychology, and pedagogy) were conducted to reduce the initial pool of 198 items to only 42 (see Table 1 in Appendix A), which made up the initial scale used for data collection. Since the 11-point response scale (0, absolutely disagree; 10, absolutely agree) has been shown to provide higher-quality data when assessing the frequency of behavior in Europe (Batista-Foguet et al., 2009), this response format was used to allow respondents to indicate their level of agreement with the applicability of the behavior described in the item to their situation. Subsequently, for the application of IRT, the range of this scale was reduced to a Likert format of 1 to 5.

2.3. Data processing and statistical analysis

The substantial size of our sample was leveraged by randomly splitting it into two equal subsamples (n = 997) to cross-validate the factor structure of the item set. First, the underlying factor structures were compared using Exploratory Factor Analysis (EFA; Maximum Likelihood Estimation and Promax rotation). Subsequently, from a confirmatory perspective, goodness of fit and factor invariance was assessed in both subsamples. Essentially, the goodness-of-fit indices recommended by Hu and Bentler (1999) and Kline (2010) were used: Satorra-Bentler χ^2, CMIN/DF, CFI, RMSEA, and SRMR.

The evaluation provided by the CFA model was complemented by the IRT perspective, which is much more suitable for assessing severity of addiction. As a preliminary step to this analysis, the basic assumption of unidimensionality for the item set was checked using standard IRT indices. Subsequently, four indices were used to quantify the addiction severity described by the items: a) the subjects' mean evaluations of the items, known as the Relative Difficulty Index (RDI, here, difficulty refers to the degree of addiction); b) the mean of the difficulty parameters; c) the discrimination capability of the items, which is highly correlated with the loadings from the previous CFA model; and finally, d) the estimated level of information provided by each item for various levels of addiction, along with the total information provided by the proposed scale.

SPSS 27.0 was used for the Exploratory Factor Analysis, and Maximum Likelihood Estimation on the covariance matrix (LISREL 11 version 11.0.3.2) was employed to provide the confirmatory perspective. To conduct the IRT analysis, the two-parameter model—difficulty and discrimination—and the information level across the continuum of the addiction construct were used.

3. Results

3.1. From the perspective of the factor analysis model

The initial exploratory and confirmatory factor analyses revealed a four-factor structure. Three corresponded to dimensions commonly attributed to substance addiction: Factor 1 (Tolerance/Control deficit); Factor 2 (Withdrawal syndrome) and Factor 3 (Negative Behavioral Consequences). The fourth factor that emerged included five items (20, 30, 31, 32, and 37) related to physical and health consequences derived from addictive SP use. However, it was possible to merge these five items with the items from the third factor of Negative Behavioral Consequences without compromising the model fit, resulting in the more parsimonious 3-factor solution. Therefore, for reasons of parsimony the 4-factor solution was omitted since the loadings pattern was identical. High correlations (from .957 to .989) between the three- and four-factor solutions across two randomly split subsamples confirmed the robustness of this structure (see Table 1). Moreover, the same structure demonstrated invariance across subsequent incremental variations in sample size (n1 = 586; n2 = 1274; n3 = 1994). Table 1 shows the maximum likelihood solution and Promax rotation of the EFA model, specifying only the 3-dimensional solution.

The results for both subsamples using the 3-factor and 4-factor solutions showed that items 22, 32, 37, 38, and 39 were excluded due to weak correlations with the remaining items and absence of theoretical justification for additional dimensions. Moreover, their content also substantively justified this decision (see Table 1). The resulting 37-item three-factor model was subsequently specified as a Confirmatory Factor Analysis (See Table 2 in Appendix A).

Considering the fit of the CFA model, we eliminated intentionally redundant items from the original set of 37. This was the case for items 1 and 7, 21 and 25, and 20, 30, and 31, which were included to identify participants who gave divergent evaluations on items with nearly identical content. Table 2 shows that we opted for the items with the highest loadings (7, 21, and 31). Therefore, at this stage, our current questionnaire included 33 items.

High correlations among first-order factors in both subsamples (Tolerance/Control deficit: .938; Withdrawal syndrome: .982 and Negative consequences: .941), as well as in the whole sample, suggested a second-order latent factor, labelled "Nomophobia" by some authors (Goncalves et al., 2020; Hartanto & Yang, 2016). Indeed, the goodness-of-fit indices did not reject the model specifying a single second-order factor, with high factor loadings of the dimensions (1st order factors) in both subsamples: Tolerance/Control deficit (.938/.929), Withdrawal (.884/.877), and Negative consequences (.853/.841).

Though relatively high, the magnitude of the goodness-of-fit indices

[2] The study was approved by ***Esade's Committee on the Use of Human Subjects in Research*** on **12/12/2024** with approval number **039/2024**

for the model (See Table 3 in Appendix A) was due to excessive power. The simplicity (parsimony) of the model, its relatively high loadings, and the large sample size in both subsamples (997 participants) contributed to inflating the usual fit indices. First, as Table 3 shows, by releasing some justified correlations between the measurement errors whose standardized values were consistently below 0.2, the value of the global indices diminished drastically. Second, the p-value for the Test of Close Fit (RMSEA <0.05) of 0.798 left no doubt about the goodness of fit for the model with three first-order factors and 1 s-order factor.

Since the item selection from the current 33 items based on the CFA model's factor loadings was identical in both subsamples, Table 3 describes the sequential process of item elimination in the overall sample, illustrated by optimization of the model's fit indices.

Thus, items 7, 9, and 12 addressed the same idea (lack of control and high tolerance); again item 7 was chosen for being shorter and having the highest loading on the first factor of the CFA model (see Table 2). Similarly, items 21 and 40 referred to negative consequences in daily work or school activities; item 21 was chosen for its superior psychometric properties. Likewise, item 15 was preferred over item 10 regarding anxiety, item 17 was chosen over items 2, 3, and 14 concerning lack of control, and item 23 was preferred over items 5 and 11 regarding the primacy of virtual relationships. From the selected set of 24 items, we allowed the estimation of four correlations between measurement errors (TE) identified by the modification indices and whose wording further justified them.

The choice of all these items was also justified from the perspective of the IRT, presented below. In this sense, the items suggested for elimination based on the CFA model were often those that IRT will show provide the least information and discriminate the least along the continuum of addiction. The CFA provided additional evidence that justified using the IRT perspective to essentially rank the items according to the level of addiction exhibited by the behavior or perception described in them.

3.2. From the perspective of the Item Response Theory

One of the main advantages of the IRT approach, derived from ordering items according to the severity of addiction they represent, is the ability to reduce the number of items needed by matching the items to the trait level of a particular individual, thereby increasing the quality of responses. The IRT model has already been used in previous research to assess scales for Internet Gaming Disorder (Gomez et al., 2019; King et al., 2023; Maldonado-Murciano et al., 2020) and for evaluating PSU (Clark & Harris, 2021; Donaldson et al., 2021).

The unidimensionality assumption, routinely required by IRT to analyze the mentioned addiction severity, was verified through standard indices. The first three columns of Table 1 include the usual IRT indices—Unidimensional Congruence (UniCo); Explained Common Variance (IECV); and Mean of Item REsidual Absolute Loadings (MI-REAL)—supporting the CFA-derived second-order factor.

Table 1 presents the ranking of the original 42 original items according to the 'difficulty' (addiction severity) indices derived from IRT, i.e., columns (e) RDI, i.e., Relative Difficulty Index; (f) Mean of the Difficulty Parameters 'bs' (i.e., the differential increase in addiction required to gain an additional point when evaluating the behavior described by the item). This ranking coincides with participants' direct ratings of the items (d). The stability in ordering items across these three classifications (only three items: 19, 31, and 38 vary slightly) indicates a robust and invariant structure.

Fig. 1 shows the relationship between each item's discrimination parameter (vertical axis) and the severity of addiction reflected by the mean of the difficulty parameters, as reported in Table 1. The mean of these coefficients b (horizontal axis) reflects how frequently the behavior described by the item occurs among university students under the age of 25 who comprised our study sample. Additionally, the color of each dot indicates the three factor sub-dimensions of the construct

Table 1
Unidimensional IRT indexes (a-c) of the sorted items according to the severity of addiction they reflect (d-f) (a) Unidimensional Congruence (UniCo); (b) Explained Common Variance (IECV); (c) Mean of Item REsidual Absolute Loadings (MI-REAL); (d) participants' direct ratings means; (e) RDI, Relative Difficulty Index; (f) Mean of the Difficulty Parameters 'bs' (g) item's discriminative ability.

Items sorted according to IRT indexes N = 1994	IUniCo	IECV	IREAL	Mean	RDI	Meanb	a
3. I use the SP when I am bored	.684	.484	.162	8.42	.884	−2.83	1.13
14. I check my SP first thing in the morning	.911	.688	.433	7.18	.773	−1.59	0.79
9. I often use the SP more time than I had planned	.927	.713	.259	6.99	.751	−1.17	1.39
12. I plan to use my SP for some time, and then I find that I have spent much more time than I intended	.916	.695	.410	6.95	.743	−1.15	1.69
17. If I am inactive for a few minutes, I instinctively tend to check my SP	.911	.687	.382	6.76	.726	−1.13	1.23
2. I often check my SP for new notifications	.916	.695	.359	6.74	.722	−1.13	1.17
1. I find it difficult to control the amount of time I use my SP	.975	.815	.350	6.34	.691	−.675	1.71
7. I find it hard to switch off my SP	.986	.857	.316	6.02	.663	−.500	1.97
13. I often find it difficult to concentrate on my tasks due to SP use	.998	.937	.291	6.08	.653	−.447	1.60
10. I feel anxiety in places where there is no coverage/ SMs are prohibited	.999	.953	.168	5.60	.621	−.260	2.01
35. I sometimes use my SP and its applications while crossing the street	.996	.915	.136	5.55	.609	−.202	0.82
6. I feel irritated if I can't look for information on my SP when I want to	1	.992	.128	5.58	.610	−.120	1.18
40. I spend time with my SP when I should be doing other things, and this causes me problems	1	.997	.048	5.04	.568	.055	1.87
39. I use my SP to update my	.999	.961	.037	4.84	.546	.267	2.07

(continued on next page)

Table 1 (*continued*)

Items sorted according to IRT indexes N = 1994	IUniCo	IECV	IREAL	Mean	RDI	Meanb	a
posts on WhatsApp, Facebook or Instagram several times a day							
29. I can't control the urge to use my SP	1	.978	.079	4.81	.545	.272	0.76
22. I often keep my eyes and hands on my SP while eating or watching TV	1	.991	.111	4.90	.541	.285	1.13
42. If I don't have my SP, I feel strange, because I don't know what to do	1	1	.051	4.62	.526	.305	1.60
33. I have tried several times to shorten my SP usage time with no success	1	.99	.004	4.61	.519	.367	1.84
18. I feel insecure when I am without my SP	1	.987	.064	4.27	.495	.457	2.01
25. Using my SP affects my daily life (work or studies)	1	.988	.069	4.31	.493	.462	1.37
36. I feel the need to use my SP right after I stop using it	1	.997	.066	4.33	.495	.510	1.32
28. I feel like I can't live without my SP	1	1	.039	4.28	.489	.582	1.40
21. I don't do what I should do at work, school or at home because of my SP	1	.986	.006	4.17	.477	.600	1.49
41. I am unable to separate myself from my SP	1	.993	.075	3.94	.463	.752	1.83
15. I feel anxious or uneasy if my SP is not within reach	.999	.968	.057	3.96	.448	.830	1.63
32. I have eye discomfort caused by excessive SP use	.999	.951	.125	3.75	.441	.840	1.26
27. I overuse my SP even though I realize its adverse health/physical effects	.997	.93	.130	3.74	.438	.922	1.44
26. I use my SP to forget about real life	.987	.862	.205	3.77	.436	.990	1.10
19. The social media applications on my SP allow me to dispense with personal interactions	.971	.801	.231	3.55	.427	1.06	1.47
20. I have some trouble sleeping due to excessive SP use	.986	.854	.233	3.59	.425	1.06	0.94
30. I have slept less than 4 h more than once due to SP use	.998	.934	.118	3.57	.424	1.07	1.23
16. My family or friends complain that I use my SP too much	1	.988	.061	3.40	.418	1.16	1.24
38. Using my SP has put me in dangerous situations, e.g., while driving	.997	.933	.094	3.43	.417	1.25	1.24
31. I feel tired and don't get enough sleep due to excessive SP use	.988	.863	.249	3.07	.413	1.39	1.31
8. I get angry/ irritated when someone bothers me while I'm using my SP	.989	.869	.226	3.59	.408	1.42	0.94
37. I feel dizzy and get headaches from prolonged SP use	.997	.923	.162	2.67	.372	1.89	1.15
34. I think life without SP would be boring, empty and sad	.964	.783	.231	3.08	.368	2.02	0.90
5. I feel closer to the people I meet through my SP than to people in the real world	.762	.54	.233	3.57	.348	2.08	0.67
24. My SP use has jeopardized an important relationship or academic/ work opportunity	.901	.674	.349	2.79	.328	3.43	0.69
11. I would rather talk with my friends/family on my SP than go out with them	.261	.213	.505	1.66	.253	3.62	1.04
23. I often stop going out with my friends to spend more time using SP	.456	.339	.562	1.75	.251	3.63	1.35

(*continued on next page*)

Table 1 (*continued*)

Items sorted according to IRT indexes N = 1994	IUniCo	IECV	IREAL	Mean	RDI	Meanb	a
4. When I sleep, I dream that I am using the apps on my SP	.847	.615	.284	1.58	.241	5.62	0.99
	(a)	(b)	(c)	(d)	(e)	(f)	(g)

'addiction' each item is associated with. In contrast, the size of the dot represents the level of information that each item contributes to the construct (i.e., the area under the information curve; see Fig. 2)

Fig. 1 highlights six key patterns in how the items functioned. First, the items were distributed along the horizontal axis according to their level of addiction severity. Items related to Tolerance/Control deficit (red) clustered at the lower end of the continuum, those related to Withdrawal syndrome (blue) appeared in the mid-range, and items reflecting Negative consequences (green) were positioned at the highest severity levels. Second, regardless of the level of addiction these items represented, they were distributed throughout the entire discrimination range (vertical axis). Notably, items from the Tolerance/Control deficit dimension exhibited higher discrimination values and provided a medium or high level of information.

Third, the items that truly indicate prominent levels of 'addiction' were those associated with the third factor subdimension -Negative consequences-which tended to be more extreme, and, therefore, less informative. Fourth, the items related to Negative consequences and Tolerance/Control deficit referred specifically only to SP use, which explains their occurrence across the discrimination range and their association with all levels of addiction. In contrast, the items describing Abstinence Syndrome -second factor (blue dots)- were generally positioned around the midpoint of the severity scale, as they captured broader emotional states commonly experienced in everyday life, not solely in the context of SP use.

Finally, as also observed by CFA, several items with highly similar content—appearing in proximity in Fig. 1—suggested conceptual redundancy. These clusters (pairs, trios, or quartets) were candidates for elimination in our item-reduction process, which aimed to enhance the scale's parsimony without sacrificing psychometric quality.

Fig. 2(a) provides additional insight into item selection by displaying the item information curves for the original pool of 42 items initially proposed. The horizontal axis represents the continuum of SP addiction, while the vertical axis reflects the amount of information each item contributes. For example, item 24 (last item in the second row of Fig. 2 (a)) provided little information for positioning an individual on the addiction scale; if included, it would be more informative at higher levels of addiction. In contrast, item 12 (last in the fourth row) would provide more information for discriminating among low/middle addiction values. Note that the items located in the last two rows tended to provide the most information overall and were effective across the full spectrum of addiction severity. The usual sequential presentation of questionnaire items in an adaptive test, like the one we propose, allows us to clearly place an individual in a segment of addiction, which can then be further refined using the most informative items in that segment.

The combination of information in Fig. 1, Table 1, and Fig. 2, together with the results of the previous CFA model, guided the selection between the items that would make up a much more parsimonious measurement model. In addition to the items that reflected uncommon behaviors, which the previous CFA model had already initially ruled out (items 22, 32, 37, 38, 39), the last two columns of Table 1, along with the information from Fig. 2, led us to retain the following items, as was also the case with the CFA model: 7 (and discard: 1, 9, 12); 15 (and discard 10); 31 (and discard 20 and 30); and 21 (discarding 25 and 40). In fact, both Fig. 2 and Table 1 show that the four chosen items were much more informative and discriminated better than the eight discarded items.

In addition to items flagged for elimination by the prior CFA model,

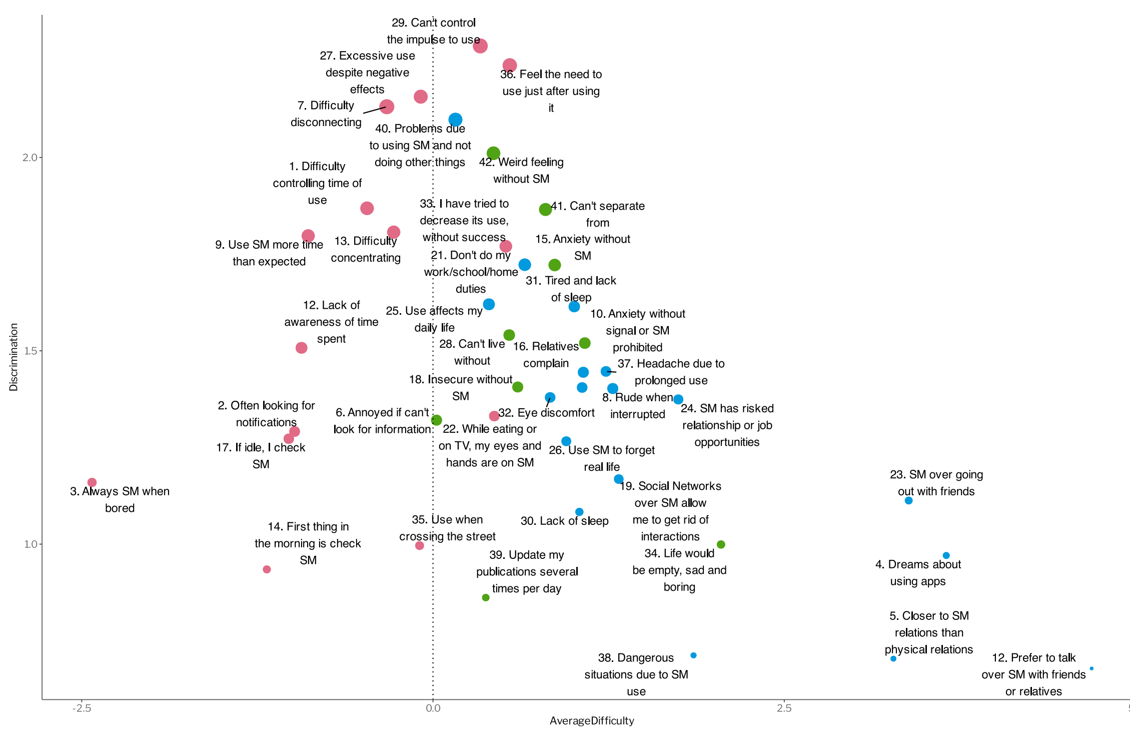

Fig. 1. Difficulty (average of "b" parameters) vs Discrimination. Colors represent the dimensions, and the size of the dot represents the amount of information (according to the ICI, Information Curve Integral). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

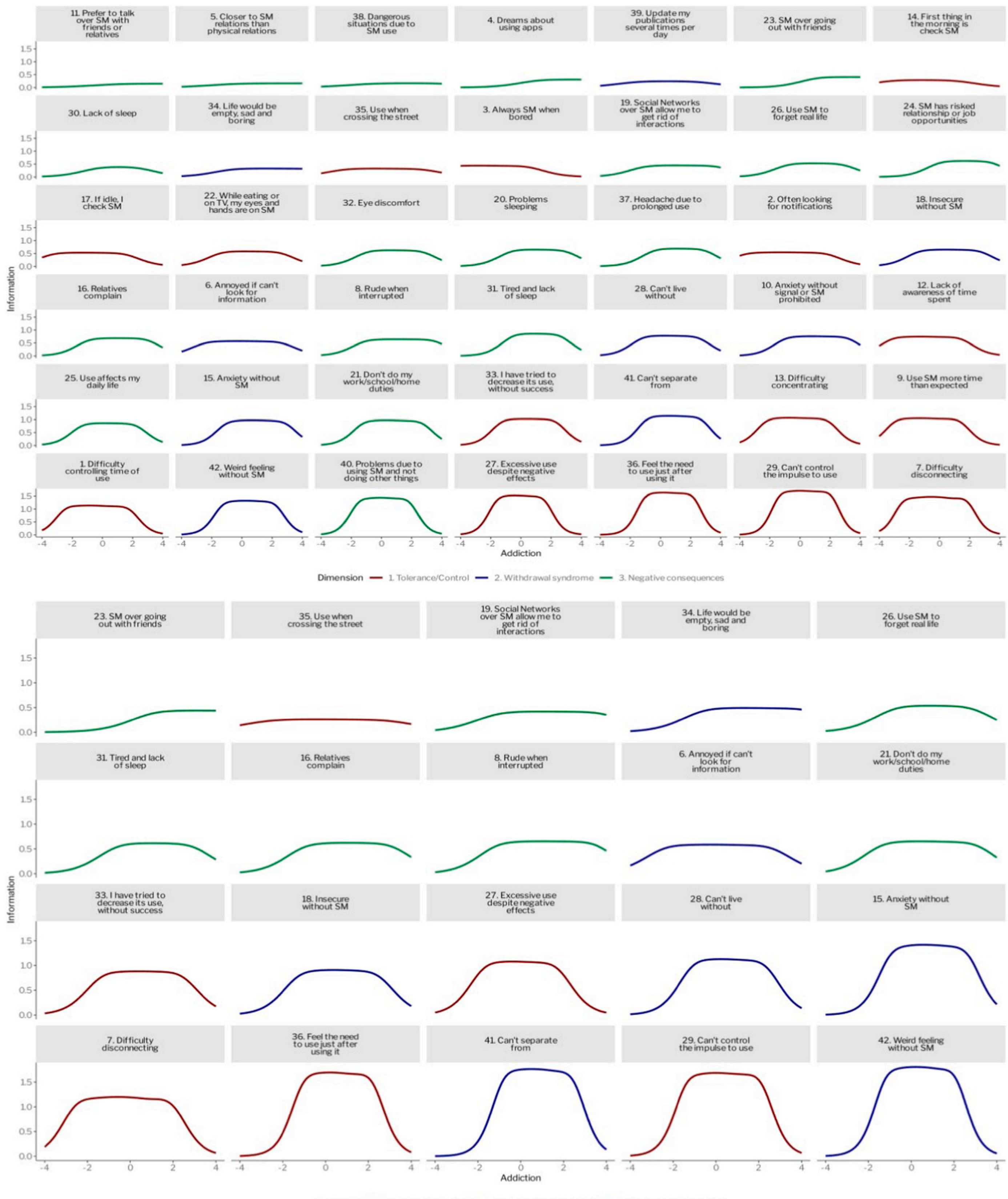

Fig. 2. (a) Information curves for the original 42 items, and (b) of the 20 items from the final survey and dimensions containing Tolerance/Control deficit (red); Withdrawal syndrome (blue); Negative consequences (green). These Item Information curves are sorted by total information (area under the information curve). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

this IRT analysis (see Table 1, Figs. 1 and 2) highlights further selection opportunities. Among the lower-end items on the addiction continuum (items 7, 13, and 17), all associated with the Tolerance/Control deficit factor, item 7 emerged as the strongest candidate for retention due to several qualities: (i) concise wording; (ii) high UniCo and IECV values (indicating strong alignment with the latent factor); (iii) low MI-REAL (suggesting less unexplained variance); (iv) moderate difficulty (Meanb = −0.500, closer to zero than item 17); (v) higher discrimination (a = 1.97) compared to items 13 and 17; and (vi) greater significant contribution to total information (see Fig. 2). Together, these qualities made item 7 the most effective and informative choice, suggesting that items 13 and 17 could be eliminated.

In the mid-range difficulty level shown in Fig. 1, we identified a cluster of items (8, 16, 19, 21, 24, 26, and 31) associated with the "Negative consequences" factor, sharing similar addiction scores (shown as closely positioned blue points). However, item 24 consistently performed poorly across IRT-based criteria, with the lowest UniCo and IECV, highest MI-REAL, and lowest discrimination (a). Its high Meanb and low RDI suggest that the item was both difficult and not broadly applicable to participants. Additionally, it provided minimal information (see Fig. 2), making it the best candidate for elimination.

Analogously, at the higher end of the continuum, among the items 23, 4, 5, and 11, which referred to the most addictive behaviors, item 23 was the best choice for inclusion (although items 4, 5, and 11 were already discarded for other reasons), since it had: (i) good alignment with Latent Trait (UniCo& IECV) without being overly specific; (ii) Low Unexplained Variance (IREAL) and the highest MIREAL (0.562), contributing more than the others to explained variance and less noise; (iii) Moderate Difficulty (Meanb, 3.63) but higher than the other items, making it valuable for identifying individuals with higher social media addiction; (iv) having a = 1.35 is better at differentiating between levels of the latent trait; (v) although all items at the top of the addiction continuum (extreme behavior) had low total information curves (Fig. 2), item 23 was the most informative on the high range of addiction, making it our top retention priority among the four items.

Therefore, our questionnaire proposal for SP addictive usage -the Smartphone Addiction Degree Estimation Scale (SADES)- has three dimensions with 6, 7, and 7 items, respectively (see Appendix B). After discarding 22 items during these 'pruning items' processes based on CFA and IRT, the results were recalculated using the much more parsimonious scale, which consisted of the 20 retained items. Fig. 3 shows the distribution of the estimated 'addiction' values for each item, along with a histogram illustrating the severity of addiction among the participants in our sample. The histogram shows that the range of the distribution went from −3 to slightly above 3. The kurtosis was 0.61, indicating a leptokurtic distribution with elongated tails that incorporated more outliers than expected. In fact, values just below 3 and up to the maximum (3.84) suggested severe addiction problems.

Using the properties of the IRT, which places the addictive behavior described by the items and the estimated addiction of the subjects on the same scale (see Fig. 3), allowed us to overlay the items (along with their dimensions) on the histogram. This clearly determines which items are best suited to assess different segments of the addiction promoted by the SP. Furthermore, note that the items ordered according to IRT (Appendix B) led to sequencing our latent dimensions according to whether they signposted a less addictive (F1: Tolerance/Lack of Control) or more addictive (F3: Negative consequences) level.

3.3. Assessing the psychometric properties of the 20-item scale

To evaluate the measurement quality of the questionnaire, we first examined the unidimensionality of each three addiction dimensions, as shown in Table 2. Given the similarity of means and variances, this provided a 'rule of thumb' test for tau-equivalence, enabling us to assess reliability using Cronbach's alpha. Additionally, we calculated Heise and Bohrnstedt's Ω (Heise & Bohrnstedt, 1970), a simpler alternative that only requires unidimensionality. Both methods yielded nearly identical reliability estimates (.857/.860; .871/.875; .818/.825), which strengthened confidence in the unidimensionality of the dimensions. Otherwise, if unidimensionality were not fulfilled, the alpha coefficient would have been biased (Raykov, 1997).

Table 2 shows that—even with high statistical power—the global fit indices (columns a–e) all fell within acceptable thresholds, indicating that our three unidimensional Factor Analysis models led to a correct fit of our data, i.e. of our three covariance matrices (Credé & Harms, 2015).

However, in order to avoid the so-called "fit index tunnel vision" problem (i.e. focusing only on indices of overall model fit and statistical significance) at the diagnostic stage, we used more nuanced diagnostic indicators, including: (1) reasonable estimated values in the expected direction; (2) theoretically justified correlated residuals; and (3) the evaluation of modification indexes alongside their expected parameter changes, which contributed to more plausible estimates. This approach, aligned with Saris et al. (2009), considers both significance and test power, the magnitude of the residuals, estimates, and emphasizing the detection of misspecification errors (columns g, h in Table 2) over simply achieving a good global fit. The identified misspecifications (column h) were attributed to either incidental parameters or test-specific sensitivity. Moreover, none of these detected misspecifications were plausible.

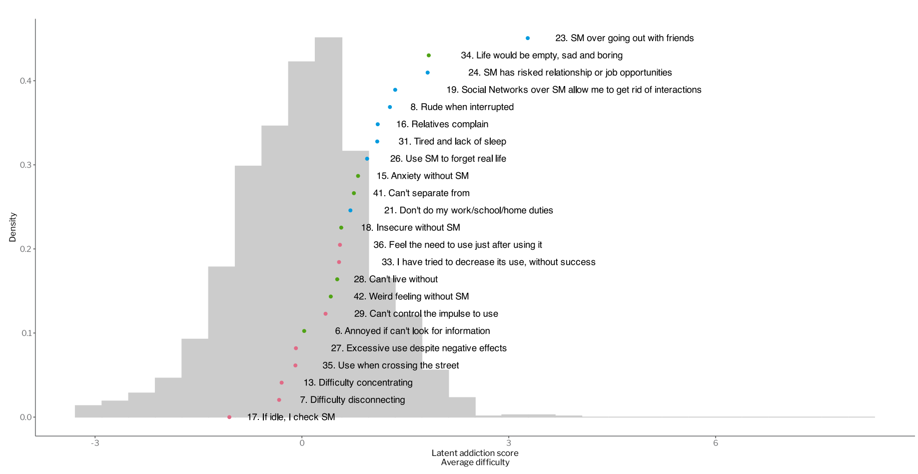

Fig. 3. The histogram for the distribution of addiction scores in the university population and over imposed severity of addiction (Density) associated with each item of the 20 selected items that make up the final questionnaire.

Table 2
Unidimensionality test for the three smartphone addiction dimensions of SADES.

Dimension	$SB\chi^2$(df)	RMSEA	CI_{RMSEA}	PCl	CFI	SRMSR	Missp*	Missp>.10
Toler_Ctrl_F1	23 (8)	.033	.019; .048	.964	.994	.0141	1	0
Withdr_Synd_F2	37 (10)	.038	.026; .051	.922	.997	.0168	2	0
Neg_Conseq_F3	38 (11)	.0364	.024; .049	.961	.994	.0193	2	0
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)

3.3.1. Evaluation of SADES performance in assessing gender differences

In our study, since the results and conclusions were very similar with both the original 42-item and short 20-item scales, we present only those pertaining to the latter, i.e., the proposed 20-item SADES scale.

To compare scores on these dimensions between genders, we first conducted a sequential test of measurement invariance to ensure the items were factor equivalent. We began by evaluating the extent to which the items in each dimension fit the same unidimensional factor model with the same loadings and intercepts i.e. configural, metric (measurement unit equivalence) and scale invariance, regardless of gender.

Table 3 presents the results of a three-factor model in which factor loadings and then intercepts are constrained to be equal for men and women. Although, as previously mentioned, excessive statistical power may inflate goodness-of-fit indices like $SB\chi^2$, leading to relatively high values, these do not warrant the rejection of factor equivalence. The configural test supported the hypothesis that the three constructs were conceptually equivalent across groups; in other words, the same Confirmatory Factor Analysis (CFA) model fit both groups. Strong metric equivalence was not rejected either, meaning that equality constraints on factor loadings and intercepts held. Despite the high statistical power, the chi-square change test was not significant, and all global fit indices (except SRMR) actually improved in this more constrained model. In fact, the overall pattern of findings -including the improvement in other goodness-of-fit indices with the introduction of equality constraints, the small magnitude of residuals, the plausibility of the parameter estimates, and the absence of misspecification errors-supports the conclusion that the semantic interpretations of the items and the factor equivalence were not meaningfully different across men and women.

Cheung and Rensvold (2002) noted that fit indices are overly sensitive to model misfits -such as slight deviations in intercepts-when transitioning from configural to strong metric invariance testing. Once strong factor invariance was established, we could assess the impact of constraining the latent means of the addiction dimensions to be equal across groups (men and women).

Although we are aware that this sensitivity is exacerbated when group sample sizes are unequal, as in our case, making it more challenging for the data to meet the required assumptions, the more constrained model with equal latent means of men and women was clearly rejected. The last row of Table 3 shows a significant change in the robust χ^2 statistic, indicating genuine differences in latent factor means between genders. The following two tables show the details of these differences.

Since gender constraints lead to comparing nested models, we used the chi-square increment test, $\Delta SB\chi^2$(df), plus other usual indices' increments, to assess whether the fit of the simpler (constrained) model significantly worsened the model fit. Akaike Information Criterion (AIC) and its variant, the Consistent Akaike Information Criterion (CAIC), are used as supplementary tools that focus on parsimony. Although they do not test statistical significance in fit differences, the lower values of the non-constrained model and the chi-square increment corroborated our previous results on gender differences in SP addiction. These results can be observed in Table 4.

Table 5 presents the means, standard deviations (the response range of the items being 0-10), comparison of means, *t*-test, and other non-parametric tests (having identified some outliers in both samples), and effect sizes for gender differences in SP addiction for the 697 male and 1297 female university students surveyed. These data reveal that Tolerance/Control deficit always had the highest mean, then Withdrawal syndrome, and finally Negative consequences. Statistically significant differences were found between genders, both for the overall addiction score and for the dimensions of Tolerance/Control deficit and Withdrawal syndrome. Women displayed significantly higher means than men in both of these dimensions, while no differences were observed for the Negative consequences dimension. Nevertheless, all effects sizes (Cohen's d) would be interpreted as small according to conventional benchmarks.

The detected pattern of higher means among women did not extend to the third addiction dimension, Negative consequences (F_3). However, a closer examination of the results sheds light on the non-significant effect of gender observed within this dimension. Out of the seven items in F_3, women scored higher on two (items 26 and 16), while men scored higher on three (items 23, 24 and 31), the remaining three items not being significant in relation to gender differences. This polarized, gender-specific pattern appears unique to this factor and may mask overall gender differences in the negative consequences of SP use. To further clarify these differences, Table 6 presents the fifteen specific items that displayed the most significant differences by gender (sorted by *t*-test).

A Structural Equation Model was employed, first to illustrate the existence of SP addiction as a second order factor from Tolerance/Control deficit; Withdrawal syndrome and No awareness about the negative consequences, and second to assess the specific effect of gender on the three components of SP addiction (Fig. 4 and Table 7). The results in Table 7 (columns g and h) confirm a significant gender effect: women tend to exhibit higher levels of severe Tolerance-Control deficit and withdrawal issues, while now men are more likely to display a significant lack of awareness about consequences.

Finally, to further illustrate these findings, the percentile scores by gender offer additional context to better understand SP addiction prevalence among young university students. This approach not only provides more in-depth insight into gender-based patterns but also enriches the analysis of addiction behaviors within each specific dimension. The percentiles shown in Table 8 are worthy of note. Contrary to what we have just shown, "on average" (Nomophobia, column d versus column h) -with comparison of means and SEM-men tend to exhibit higher levels of SP addictive behavior than women in all dimensions.

Table 3
Factor Equivalence test for the SADES three-factor model.

20-item scale	$SB\chi^2$(df)	RMSEA	CIRMSEA	P-v CloseFit	PNFI	CFI	SRMSR	GFI
Configural Equiv	997 (322)	.0463	.0430.0496	.969	.832	.969	.0367	.942
Strong Metric Equiv	1028 (343)	.0452	.0420.0484	.994	.895	.987	.0417	.942
Equal latent means	1682 (370)	.0602	.0573.0631	.000	.890	.970	.0429	.935

Table 4
Global fit indexes of SADES by gender.

Scale dimension	Mean Constr	$\Delta SB\chi^2$(df)	ΔRMSEA	ΔCFI	ΔSRMS	ΔAIC	ΔCAIC
		57 (3)	.001	.000	.01	51	31
TolerCtrl_F_1	6.15						
WithdrSynd_F_2	4.07						
NegConseq_F_3	3.46						

Unconstrained mean estimates by gender are presented in Table 5.

Table 5
Means and standard deviations of the three dimensions, Independent-Samples *t*-test, Median Test, Mann-Whitney *U* Test, Kolmogorov-Smirnov Test and Kruskal-Wallis Test for differences in SADES by gender.

Dimension	Gender	Mean	SD	t-value	Median Test- χ^2	Mann-Whitney U	Kolmog-Smirnov	Kruskal-Wallis	Sig	Cohen's d
TolerCtrl	Men	5.85	1.76	−5.39	14.62	4.99	2.54	24.87	<.001	.272
	Women	6.36	1.81							
	All	5.68	1.82							
Withdraw	Men	3.84	1.84	−4.84	12.97	6.62	2.42	21.29	<.001	.244
	Women	4.25	1.99							
	All	4.46	1.94							
NegConseq	Men	3.49	1.62	1.18	2.42	−1.16	1.10	1.35	ns	.076
	Women	3.44	1.58							
	All	3.48	1.59							

Table 6
SADES items showing the most significant gender effect.

Item and factor	*t*-test	Cohen's d	Higher scores
It18F_2. I feel insecure when I am without my SP	−9.001	−0.4227	Females
It15F_2. I feel anxious or uneasy if my SP is not within reach	−5.799	−0.2723	Females
It17F_1. If I am inactive for a few minutes, I instinctively tend to check my SP	−5.461	−0.2565	Females
It24F_3. My SP use has jeopardized an important relationship or academic/work opportunity	5.424	0.2547	Males
It23F3. I stop going out with my friends to spend more time using the SP	5.311	0.2494	Males
It35F_1. I sometimes use my SP and its applications while crossing the street	−5.230	−0.2457	Females
It26F_3. I use my SP to forget about real life	−5.158	−0.2422	Females
It42F_2. If I don't have my SP I feel strange, because I don't know what to do	−4.301	−0.2020	Females
It29 F_1. I can't control the urge to use my SP	−3.888	−0.1826	Females
It33F_1. I have tried several times to shorten my SP usage time with no success	−3.883	−0.1824	Females
It31F_3. I feel tired and do not get enough sleep due to excessive SP use	3.500	0.1644	Males
It28F_2. I feel like I can't live without my SP	−3.554	−0.1669	Females
It13F_1. I often find it difficult to concentrate on my tasks due to SP use	−2.764	−0.1298	Females
It27F_1. I make excessive use of my SP despite realizing its adverse physical and health effects	−2.704	−0.1270	Females
It16F_3. My relatives or friends complain that I use my SP too much	−2.673	−0.1255	Females

And if we take a deeper separate look into the percentiles of the three components of Nomophobia, additional nuances emerge. Let us first focus on the contradictory third dimension of Negative consequences (columns c and g). Here, but also in the other two dimensions, we observe that men consistently show higher z-scores at any non-central percentile of the dimension, with this trend becoming particularly pronounced at more severe levels compared to women.

A quick examination of the percentiles in Table 8 reveals that while women consistently showed higher z-scores above the median (50th percentile, blue in the table) up to the 90th percentile, above this percentile, men consistently showed higher z-scores at each other level, suggesting that they experience more severe addictive behaviors in the most extreme cases (in yellow in the table). For instance, at the 95th percentile, men exhibited a higher severity threshold for all dimensions of SADES compared to women at the same percentile. This indicates that men are more likely to experience extreme levels of behavioral addiction than women, since they are found at the highest levels of the distribution. In other words, men display more pronounced addiction behaviors than women when comparing individuals in the same high-risk percentile.

In summary, as Table 4 shows, on average women scored higher than men on two of the dimensions of the scale (Tolerance and Difficulty in control on the one hand, and Withdrawal syndrome on the other). For the dimension of Awareness of the negative consequences of SP use, no significant differences were found between the two genders. However, as Table 8 shows, men stood out in the highest percentiles of the three dimensions and in the total score for the scale, i.e. it is more common for men to suffer from an extremely high level of addiction than women. On the other hand, within the dimension of Awareness of negative consequences, on average men scored higher than women for the items referring to lost opportunities for direct social contact (being with friends) or lost productivity at school or work (being tired and sleepy or having lost opportunities) due to excessive SP use. In contrast, on average women scored higher than men when it comes to SP use as an escape from an unsatisfactory real life, or in terms of friends and family complaining that they spend too much time on their SP.

Investigating these gender differences in addictive SP usage in greater depth, Figs. 5 and 6 reflect the results of the IRT analysis, which show the items' addiction levels as well as their discriminative capacity in relation to SP use comparing men (X-axis) and women (Y-axis). The high correlation values (0.92–0.95) in both figures across each dimension suggest that men and women experience similar patterns of SP addiction overall. Most data points are near the diagonal line, indicating that both genders perceive many smartphone-related behaviors with similar intensity. For example, both men and women feel equally that "life would be empty, sad, and boring without their smartphone" (It34) and “Social networking applications via SP allow me to dispense with face-to-face interactions" (It19).

The above being said, however, certain behaviors did display gender differences. Points above the diagonal line indicate that women reported higher levels of addiction, particularly for items like “I feel tired and don't get enough sleep due to excessive SP use” (It31) and “I often stop going out with my friends to spend more time using the SP” (It23),

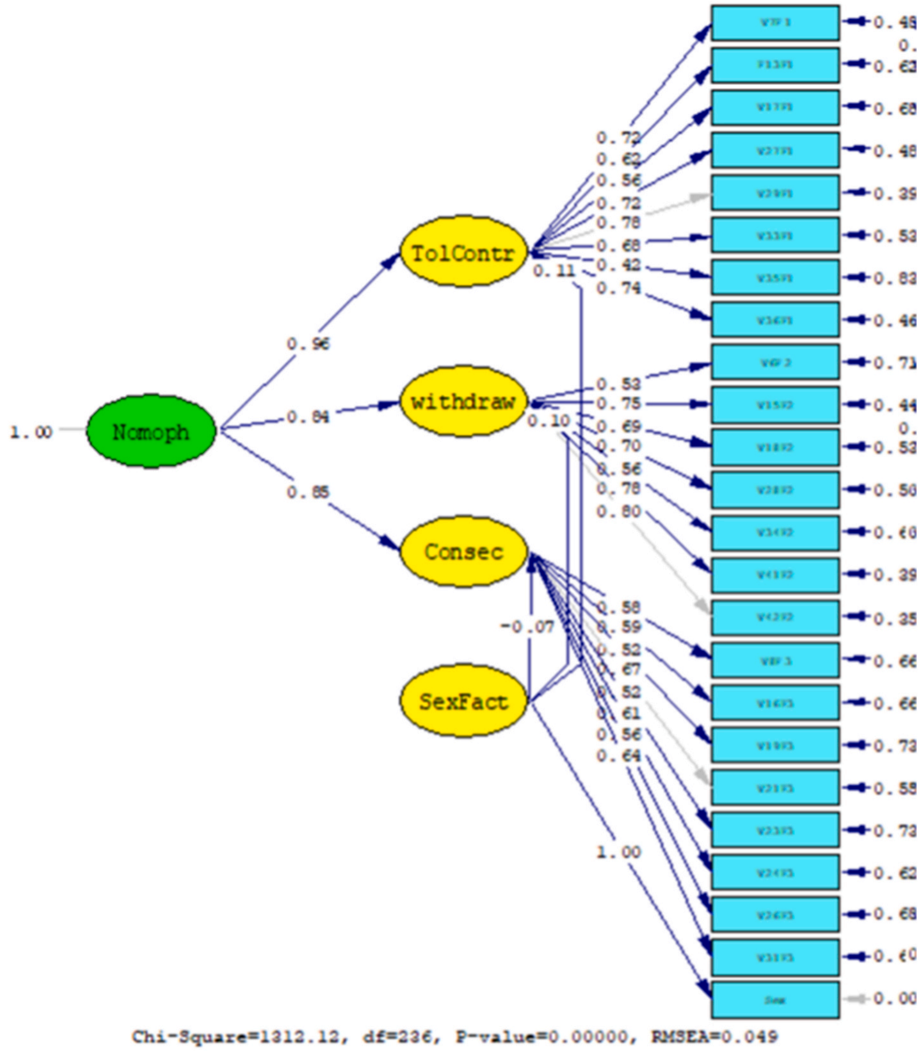

Fig. 4. Path diagram of the SADES SEM model: first-order factors' contributions to the second-order Nomophobia factor (Gamma values in Table 7) and the standardized gender effects on those factors.

Table 7
SADES' global fit indexes and gender effect on the three dimensions.

20-item scale	$SB\chi^2$(df)	RMSEA	CI_{RMSEA}	PCl	CFI	SRMSR	BetaSex	t-Value	Gamma
	1312 (236)	.0486	.046 .051	.755	.983	.0426			
TolerCtrl_F_1							−0.214	−4.458	.960
WithdrSynd_F_2							−0.221	−4.328	.851
NegConseq_F_3							0.125	2.797	.843
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)

suggesting a stronger female emotional dependency. Fig. 6 also reveals that these items are among the few that discriminate more among men than among women. In contrast, most of the points below the diagonal line in Fig. 5 show that men may engage in more impulsive or risky SP use, like "I feel insecure when I am without my SP" (It18) and "I sometimes use my SP and its applications while crossing the street" (It35) or "I use my SP to forget about real life" (It26). However, Fig. 6 shows that these addictive behaviors do not discriminate more within one gender than the other. Conversely, with regard to items 6 (F2), 33 (F1), and 42(F2) ("Annoyed if I can't look for information", "I have tried several times to shorten smartphone use but I always failed" and "Weird feeling without my smartphone"), Fig. 5 shows that men tended to report these feelings slightly more than women, even if the three exhibit far more powerful discriminating addictive behavior among women than among men. This variation in standardized scores across each dimension reveals a gender-based difference in how severity is distributed in addictive behavior.

4. Discussion

This study contributes to the extensive literature on assessing problematic SP use. Its primary goal was to develop a brief SP addiction scale suitable for use with a population aged 18 to 25, which could be flexibly applied according to the severity of addiction presented by the individual being assessed. The aim was to improve the assessment capabilities for a problem (smartphone addiction) that, according to studies conducted across a wide range of countries, currently shows a high prevalence among university students (Amin et al., 2024; Lai et al.,

Table 8
Percentiles of the three dimensions and for the total SADES score.

	MEN z-scores				WOMEN z-scores			
	TolCont	Withdr	NegCons	Nomoph	TolCont	Withdr	NegCons	Nomoph
N Valid	697	697	697	697	1297	1297	1297	1297
Percent%								
10	−1.298	−1.171	−.822	−1.219	−1.255	−1.248	−0.972	−1.286
20	−.868	−.892	−.669	−.882	−0.885	−0.915	−0.733	−0.919
30	−.519	−.612	−.558	−.548	−0.558	−0.599	−0.542	−0.566
40	−.229	−.354	−.414	−.303	−0.295	−0.360	−0.348	−0.302
50	.007	−.081	−.277	−.059	−0.004	−0.036	−0.155	−0.015
60	.234	.161	−.065	.183	0.274	0.236	0.044	0.243
70	.494	.469	.166	.493	0.533	0.546	0.313	0.529
75	.637	.649	.323	.620	0.689	0.712	0.452	0.688
80	.832	.852	.526	.783	0.855	0.888	0.654	0.862
90	1.323	1.328	1.210	1.231	1.265	1.322	1.201	1.296
93	1.422	1.503	1.648	1.492	1.454	1.490	1.460	1.551
94	1.464	1.607	1.702	1.612	1.530	1.555	1.509	1.592
95	1.575	1.865	1.866	1.713	1.590	1.637	1.648	1.676
96	1.668	1.887	2.041	1.807	1.661	1.733	1.777	1.768
97	1.831	1.976	2.352	1.962	1.737	1.846	2.063	1.824
98	2.017	2.114	2.591	2.069	1.873	1.938	2.294	2.010
99	2.165	2.343	3.162	2.490	2.105	2.066	2.701	2.167
99.5	2.334	2.551	3.824	2.838	2.233	2.277	3.117	2.352
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)

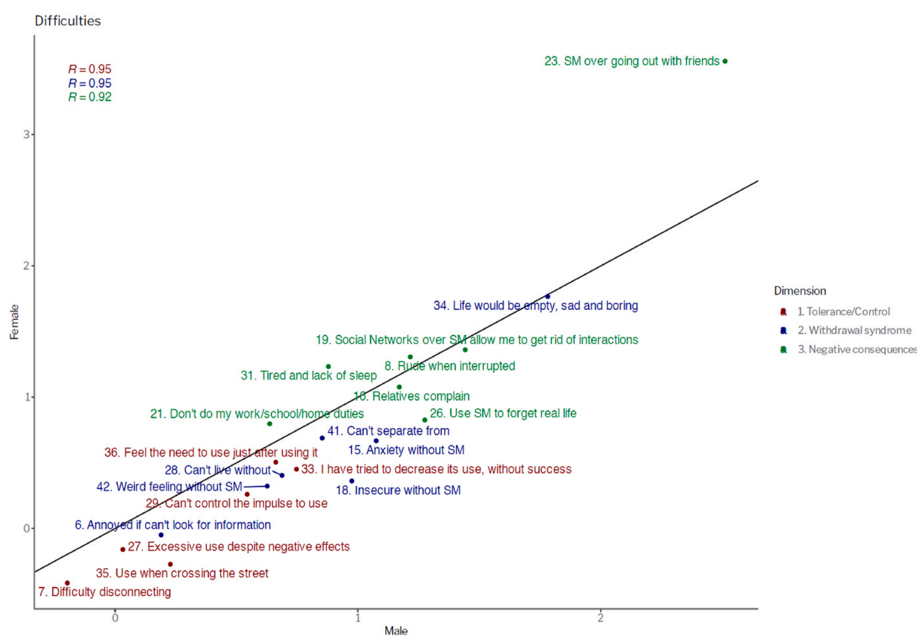

Fig. 5. Comparison by gender according to SADES score addiction level.

2025; Meng et al., 2025; Ratan et al., 2021; Song et al., 2025; Sunday et al., 2021)

To achieve this, we created the SADES scale via an unusual approach that combines Item Response Theory and conventional factor analysis, allowing us to develop a brief scale of only 20 items, which demonstrated high construct validity and reliability.

The 1.984 university students' sample is larger than in most previous studies involving similar populations. While women represented the majority, as is common in academic samples, their proportion was lower than typically observed. Therefore, this does not appear to be due to systematic reasons related to gender-based participation or response rates and, unlike previous studies (e.g., Bianchi & Phillips, 2005; Kwon et al., 2013a,b; Rutland et al., 2007), the participation of men was relatively high (34%).

Since addiction varies in intensity, it can be conceptualized as a latent variable - a second-order factor that unites the three dimensions and offers a more comprehensive view of smartphone-related addictive behavior. This perspective allowed for an alternative approach based on Item Response Theory and the conventional Factor Analysis model. In common applications of IRT, each participant's performance in relation to the knowledge being evaluated enables items to be classified from easier to harder i.e. by difficulty; in the case of PSU studied here, the items were ordered according to the level of addiction they describe. Both approaches assume that item responses are related to the intensity level associated with the construct. In IRT, this is done by relating the level to the likelihood of higher/lower values for the response, while in the FA model, it is through the correlation with the items.

From a methodological perspective, applying IRT substantially enhances validity by (a) establishing an ordering of items based on the severity of the addictive behaviors they assess; (b) tailoring the number of items to each individual's level of addiction; (c) evaluating each item's discrimination and the information it provides across the addiction

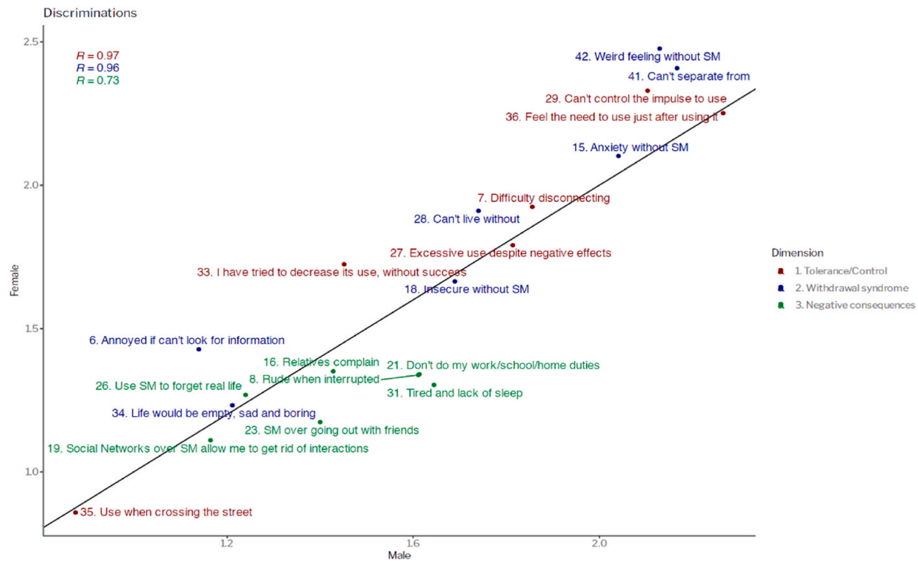

Fig. 6. Comparison of SADES discriminative power by gender.

continuum; and (d) providing a comprehensive measurement that simultaneously captures both individuals' addiction severity and the behaviors reflected in the items on a standard scale. This approach enhances our understanding of the dimensions of SP addiction and strengthens the theoretical foundations of the field. The use of both IRT and factor analysis is a promising approach for developing mental health scales (see, Keetharuth et al., 2020; Chronister et al., 2022; Lam & Lam, 2025). The 20-item SADES instrument, along with its response format, is presented in Appendix B.

Gender differences in cell phone usage patterns are widely documented in scientific literature. It is known that women spend more time on social media, while men engage more in online gaming or gambling (Billieux et al., 2007; Bouna-Pyrrou et al., 2015; Demirci et al., 2021; Kwon et al., 2013a,b; Laconi et al., 2017; Takao et al., 2009; Spilková et al., 2017; van den Eijnden et al., 2018). However, studies on cell phone addiction have also yielded divergent results. While some indicate a higher prevalence of addiction among women, others suggest the opposite, and some find no significant differences between genders (Harris et al., 2020).

In our sample of Spanish and Italian university students, we observed that women obtained higher average scores for two dimensions of the scale (Tolerance/Control deficit and Withdrawal syndrome). In contrast, in the third dimension (Negative consequences), no significant differences were found between men and women. A closer analysis of the item content revealed nuanced patterns: men tended to score higher on items related to reduced productivity and missed opportunities for in-person social interactions, whereas women scored higher on items reflecting SP use as a form of escape from unpleasant realities and perceived critical comments from family and friends regarding excessive phone use. Interestingly, although women exhibited higher average levels of PSU overall, a larger proportion of men appeared in the highest percentiles of the addiction scale. In other words, while women generally use their phones more frequently -often to maintain social connections or cope with frustration-men are more represented among the most extreme cases of addiction, suggesting a more moderate usage overall but a sharper escalation in problematic use for a subset of the male population. This pattern highlights a more severe addiction in men. Future research could investigate the factors contributing to this trend, such as academic frustration or long hours spent on video gaming. Conversely, the higher average addiction levels observed in women might be associated with factors like body dissatisfaction during adolescence (Rakić et al., 2024), higher social anxiety (Guo et al., 2025), or a stronger inclination to maintain close interpersonal relationships - often facilitated through SP use.

These results align with previous findings in the literature that associates externalized problems (such as cell phone addiction, aggression, impulsivity, and antisocial behaviors) with men. At the same time, women are more likely to experience internalized problems such as anxiety, depression, withdrawal, and somatization (Crick & Zahn-Waxler, 2003). Women also tend to be more concerned with feelings of loneliness or body image (Leal-López & Moreno, 2025). Thus, it is not surprising that cell phones have become a key communication tool for them, but at the same time, a source of distress, which can exacerbate their internalized problems (Rose, 2002).

This study not only contributes to the discourse on gender differences in cell phone addiction but also highlights how conclusions can shift depending on the methodology used. Decisions regarding which data analysis models to select have been shown to influence interpretation of the data, partly explaining the inconsistencies in results mentioned in the scientific literature. Therefore, we conducted a series of sequential analyses to illustrate how easily potentially provisional conclusions can shift depending on the analytical approach employed. For instance, a descriptive analysis of the items showed that women scored significantly higher on more items than men, which could lead to the conclusion that they have more problems related to cell phone use. This impression was further supported by factor analyses, which showed no significant gender differences in the Negative consequences factor, but did indicate that women scored significantly higher in Control deficit/Tolerance and Withdrawal.

However, the perspective provided by Structural Equation Modeling (SEM) nuanced these findings. While the result of Control deficit/Tolerance and Withdrawal was confirmed, significant differences also emerged in the Negative consequences factor. Thus, while women focused on consequences related to interpersonal relationships, men focused on more egocentric aspects, such as achievement or personal discomfort.

In addition, percentile-based analyses (robust against the effect of outliers) provided extraordinarily relevant nuances to this debate. Men were more prevalent in the lower percentiles (below the 20th), which reflects Control deficit-led cell phone use. Women predominated in the mid-to-high percentiles (50-75%), where intensive use was found. However, in the highest percentiles (above the 90th), indicative of addictive use, men were again the majority.

This percentile-based approach provides a more detailed perspective than the previous ones based on means comparison or SEM and may help reconcile divergent previous results in the literature of gender differences in internet use and SP addiction.

All of the above raises an important question: Are these interpretations of the same data due to using non-resistant descriptive statistics or SEM? Or do they reflect the presence of exceptional or atypical cases that are statistically influential but have no effect on the percentile distribution of our SADES scale, even if they are clinically relevant? This merits further discussion, as these extreme cases are precisely those that warrant more clinical attention and targeted intervention, given that they represent the most concerning patterns of use. Our study could suggest that while PSU affects both genders in similar ways overall, and in some respects may impact men slightly more at the highest levels, gender-specific intervention strategies could help address both the prevention of intensive use as well as those behaviors our analysis has identified as severe.

5. Implications for practice

Ever since the SP was integrated into everyday life, studies have been conducted on its use and the platforms it enables access to, typically developing scales to assess problematic use in the general population. However, the relevance of age in its use suggests that such research should focus exclusively on one age segment, specifically 18-to 25-year-olds. This is the predominant age at which cases of addiction to digital technologies are currently arriving at mental health centers and addiction treatment facilities to seek treatment (Aljomaa et al., 2016). The proposal presented here represents a first step in this direction, as we are currently working to adapt the SADES to adolescents and pre-adolescents, which may be of even greater interest. In these populations, early detection of the issue may prevent the need for clinical care through targeted prevention interventions.

The SADES scale stands out for its brevity compared to previous questionnaires, as only the most discriminative and informative items have been selected. Its conciseness makes it ideal for large-scale -and particularly epidemiological-studies by shortening administration time, reducing dropout rates, and minimizing participant fatigue and disengagement.

Additionally, the questionnaire's adaptive nature allows for it to be tailored to the characteristics of the population being studied. This flexibility offers significant advantages in various contexts, especially clinical settings, enabling the test to be adapted to the specific characteristics of the individual being assessed. For example, items that indicate greater severity may be more relevant for those with SP addiction, while more general items might take priority in cases where there are no severe symptoms and the aim is to simply explore SP use.

The combination of a versatile questionnaire suitable for use with large samples of emerging adults in resource for evaluating SP addiction. It covers a range of situations, from risk scenarios where preventive intervention is needed to cases that require therapeutic intervention due to their severity and interference in the person's life. This would also facilitate the public health system's implementation of protective policies and epidemiological studies and for a more individualized approach in clinical settings makes this tool a valuable regulations regarding this issue. In short, it would facilitate early detection, as well as treatment planning and symptom assessment in the clinical setting. Moreover, problematic cell phone use among young people is expected to continue to rise (e.g. among adolescents from 7% in 2018 to 11% in 2022; Boniel-Nissim et al., ?2024), so it is desirable to have cost-effective measurement tools that monitor this indicator and assess the impact of any preventive measures that may have been adopted; SADES would be very useful for these purposes.

The gender differences revealed in our study suggest that previous results in the literature may be due to various factors, including methodological differences in studies (such as sampling systems, the scale used, or the perspective of the data analysis model) and differences in the social reality studied. Ultimately, the probability of cell phone addiction may be influenced not only by personal characteristics but also by socially determined factors; this would require further research. Factors such as the age at which one starts using a cell phone, the social prestige associated with its use, social pressure to use it in academic or professional settings, dissatisfaction with oneself (with one's body image, for example), standard of living compared to others, or cyberbullying, among others, are undoubtedly important to an explanatory model of SP addiction.

Our results have the following potential implications: (1) The difference in z-scores may indicate that addictive behavior manifests differently across genders, with men potentially at greater risk of reaching high severity in Negative consequences, while women may show higher severity levels in the other two dimensions; (2) These findings could be valuable for developing gender-sensitive interventions, as men and women in high-risk percentiles might benefit from tailored support strategies that address their specific risk profiles.

Finally, it is essential to collect data that offers strong evidence for assessing potential SP addiction and its dimensions. Such evidence will be crucial when future revisions of the DSM-5-TR (American Psychiatric Association, 2022) and ICD-11 (World Health Organization, 2019) are undertaken, enabling informed decisions about the inclusion and classification of this condition.

6. Limitations and directions for future research

This study is not without its limitations. It was conducted exclusively with university students, so it will be necessary to analyze what happens with young people of similar ages with different levels of education. Secondly, the study does not identify the specific applications used by the most problematic users (Panova & Carbonell, 2018). For example, social media addiction, short-form video addiction, and gaming addiction may exhibit very different characteristics. Future studies should consider the contribution of these applications to PSU.

Thirdly, the instrument is based on self-assessment; however, this does not rule out the possibility of cross-validating certain items with input from close contacts, should complementary data be collected (Geyer et al., 2021). Fourthly, mental disorders such as depression, anxiety, loneliness, low self-esteem, and difficulties in impulse control that may influence PSU were not considered. This short scale can facilitate future confirmation, in larger and more diverse samples, of whether PSU varies significantly according to purpose, accompanying emotional states, or temporal patterns of use, as suggested by previous studies employing other scales.

Finally, although the proportion of male participants was higher than in similar previous studies, it remained lower than that of women.

Regarding the study's strengths, we would highlight the sample size and the fact that it was collected from various universities in two southern European countries. Moreover, the data were refined by removing subjects with contradictory responses to similar items.

Concerning the data analysis strategy followed, the combination of Confirmatory Factor Analysis and Item Response Theory significantly enhances and provides SADES with great power as a measurement instrument. Secondly, this "adaptive test" provides participants with a low-cost response (in terms of time and effort) and quick evaluation by the researcher or clinician. Even when the full scale is used, its brevity and careful design will enable the collection of high-quality data in future studies on SP addiction across diverse populations in this or other similar age segments. This brief and precise instrument could be of particular interest in the field of epidemiology or public health, facilitating the implementation of protective policies and regulations by the public health system regarding this issue. Also, it will facilitate early detection, treatment planning, and symptom evaluation in the clinical field.

Finally, the instrument presented in this study opens exciting future lines of research, such as the analysis of invariance based on gender, socioeconomic status, and culture; its adaptation to other life cycle stages; use for epidemiological purposes; and combining it with qualitative interviews that explore users' experiences in depth. It would also be interesting to verify whether individuals who identify themselves as addicts present a significantly different SP usage pattern from those who do not.

7. Conclusions

The study findings suggest that the combination of CFA and IRT offers a robust framework for developing a concise and practical scale to assess SP addiction young adults aged 18-25. The 20 items on the IRT-based SADES are composed of three factors: Tolerance/Control deficit, Withdrawal, and Negative consequences. Notably, items related to Negative consequences emerge as the strongest indicators of high addiction levels.

When applied to the study of gender differences, the SADES reveals that men tend to score higher on items associated with loss of productivity and diminished opportunities for personal interaction. In contrast, women score higher on items reflecting the use of smartphones for social contacts and perhaps as an escape from an unpleasant reality. An additional finding is that, although the overall prevalence of PSU is higher among women, men are more prominently represented in the higher percentiles, which indicate severe addiction.

Thus, SADES is a concise and reliable tool for assessing SP addiction, specifically targeting young adults aged 18-25. Designed for large-scale epidemiological studies and clinical settings, the tool adapts to individual characteristics and effectively measures addiction severity. Its brevity results in less fatigue among respondents, ensuring high-quality data. Despite some limitations, such as focusing on university students, the study's strengths include a large, diverse sample and robust data analysis using Confirmatory Factor Analysis and Item Response Theory. Future research could explore gender, cultural, and socioeconomic factors and adaptations for other age groups.

CRediT authorship contribution statement

Joan Manuel Batista-Foguet: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rosario Martínez-Arias:** Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation. **Xavier Carbonell Sánchez:** Writing – review & editing, Writing – original draft, Supervision, Investigation, Data curation. **Xavier Fernández-i-Marín:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Data curation. **Ana Adan:** Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation. **Ramon Mendoza-Berjano:** Writing – review & editing, Writing – original draft, Visualization, Investigation, Data curation. **Carmen Moreno:** Writing – review & editing, Writing – original draft, Visualization, Investigation. **Arnau Carmona-Feliu:** Writing – review & editing, Writing – original draft, Visualization, Data curation. **Jan Ivern:** Writing – review & editing, Writing – original draft, Validation, Investigation, Data curation. **Laura Cortellazzo:** Writing – review & editing, Writing – original draft, Supervision, Data curation. **Inés Losada-Cavestany:** Writing – review & editing, Writing – original draft, Validation, Data curation.

Data availability statement

The data supporting the findings of this study are available upon reasonable request from the corresponding author, Joan Manel Batista-Foguet, and for the purpose of more comprehensive joint exploitation of the data.

Declaration of the use of AI

Artificial Intelligence was only used for minor grammatical checks with full author oversight.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chbr.2026.101028.

Data availability

Data will be made available on request.

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