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**Predictors of problematic internet use
in the everyday internet activities of a French representative sample:
The importance of psychological traits**

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1. Introduction

Recent years have seen growing concern about excessive use of the Internet in some individuals, and the detrimental effects of such overuse. This phenomenon is labeled in the academic literature as Problematic Internet Use (PIU).

1.1 Overview of Problematic Internet Use (PIU)

According to Caplan (2007), PIU refers to a behavioral disorder based on compulsive and excessive Internet use that interferes with the activities of daily life. PIU is characterized by the following set of symptoms (Griffiths, 2005): (1) salience of Internet activities, which become dominant for the individual, (2) change in mood after engaging in Internet activities, (3) increase of tolerance, driving the individual to increase engagement in Internet activities over time to achieve the same feelings or state of mind, (4) the experience of a psychological, or even physiological withdrawal, which occurs when the individual is deprived of the use of the network, (5) rapid reinstatement of the problem behavior, (6) presence of conflicts in relation to the addictive behaviors, which may be intrapsychic (loss of control, loss of self-esteem) or interpersonal (conflicts with others in the school or work environment).

As regularly pointed by authors (Billieux, Maurage, et al., 2015) PIU involves functional impairment with tangible negative outcomes at the individual, professional, or personal levels. The potential for PIU to negatively affect mental health makes it important to better understand the predictors of problematic use in individuals: this could help at-risk individuals, either through better identification techniques or by tailoring specific policies to protect them. Examining possible predictors of PIU was the focus of the present study.

1.2. Theoretical framework for problematic Internet use

The Interaction of Person-Affect-Cognition-Execution (I-PACE) model (Brand et al., 2019; Brand et al., 2016) is the framework most commonly used to understand PIU. The I-PACE model assumes that Internet-use disorders result from a combination of neurobiological and psychological factors that interact with behaviors in a given situation. The core characteristics of a person (including their personality, genetic factors, psychopathology, etc) influence the way the person perceives their situation (such as the presence of interpersonal conflicts or excessive stress), leading to a series of affective responses (such as craving for a particular online activity, possibly as a way to cope with stress) and cognitive responses (such as attentional bias towards online activities), and ultimately to the decision to engage in (problematic) online behaviors. Over time, the individual gradually learns to associate situational triggers with specific online behaviors and specific behaviors with gratification, leading to downregulation of inhibitory control, an increase in craving, and a more impulsive and more habitual decision to engage in online activities.

Most of the I-PACE framework is applicable to both online and offline activities: the model is useful to understand both addiction to Internet activities, and addiction in general. Behavioral addictions such as pathological gambling, or pathological sex have core symptoms similar to PIU (Brand et al., 2020), and may derive from common etiological mechanisms promoting a transition from reflexive to impulsive decisions to engage in addictive activities through downregulation of inhibitory control and an increase in craving (Castro-Calvo et al., 2022). However, there may be some differences. Compared to offline behaviors, the initiation and maintenance of PIU could be related to media-specific aspects: a number of features of online activities – availability, accessibility, protection of privacy, options to deliver reward, intermittent reinforcement, affordability – are likely to accelerate the development of addictive behavior (see Brand et al.,

2019). Certain psychological processes could also have more influence in the context of problematic online activities, partly due to the design of these activities (Billieux, Philippot, et al., 2015): for example, in many Internet activities like social media or gaming, platforms are designed to convey the impression that an individual is missing out on the activities or achievements or friends, which could place more emphasis on social anxiety. This means specific investigation of PIU is warranted, as a complement to existing works about offline addictions.

Although the I-PACE model is a useful attempt to provide an overview of possible causal factors, which may be of interest in providing therapeutic interventions, it has never been tested empirically as a whole. Such an empirical test would be difficult to achieve given the breadth of the model: dozens of neurobiological, affective, conative and situational variables are potentially involved in the process. Among these, the core characteristics of a person that could serve as determinants of subsequent steps of the model have been relatively understudied. In particular, socio-demographic determinants like sex, age, educational attainment or income, could be involved in patterns of use that will shape the decision to adopt a specific behavior. Psychological traits of personality are thought to play a major role, but they too have not been systematically studied. In the next sections, we review likely socio-demographic and psychological correlates of PIU which were the focus of the present study.

1.3 Socio-demographic correlates of PIU

A number of studies have examined how socio-demographic variables can play a role in problematic patterns of Internet use. This is especially the case for sex, age, educational attainment and income – as well as cultural differences (e.g. Cheng & Li, 2014), which are not relevant to our country-specific study and will not be reviewed here.

1.3.1 Sex

Sex has probably been the most studied socio-demographic variable. Overall, men are reportedly more likely to develop PIU than women (see for example Anderson et al., 2017; Demirer & Bozoglan, 2016; Kuss et al., 2014; Müller et al., 2016). For Mei et al. (2016), this increased risk could come from the types of activities men engage in online, some of which could be more addictive than others: examples include cybersex or online gambling. Men appear to demonstrate more problematic use of video games and online pornography than women (Dufour et al., 2017; Kim et al., 2020; Tang et al., 2017 for example). Conversely, in the case of problematic uses of smartphones, Gentina et Rowe (2020) showed in a population of adolescents that women using social networks were more likely than men to be addicted to smartphone use (see also Kuss & Griffiths, 2017). Overall, being a man may be associated with higher scores in PIU in almost all activities with an exception for social media, which should be significantly higher among women.

1.3.2 Age

Age also seems to play an important role in the onset of UPI. The age group most at risk seems to be 18-25 year-olds (Kuss et al., 2014). One meta-analysis (Yu & Sussman, 2020) showed that younger people were more affected than other age groups by the problematic use of smartphones. These results may be taken as the reflection of either age-related differences of psychological vulnerability to problematic use, age-related differences in patterns of internet or smartphone use (such as more social connections with other smartphone users in adolescents and young adults), or both. Overall, younger people may demonstrate higher PIU scores in general, and especially for gaming and social media problematic uses.

1.3.3 Educational attainment

There seems to be a negative relationship between educational achievement and PIU, especially for adolescents. For example, a meta-analysis of Anderson et al. (2017) reported small negative associations between academic performance and PIU behaviors. The authors stressed, however, that the effects seemed to vary across development. A similar conclusion was obtained in the meta-analysis of Kates et al. (2018), who observed that smartphone use had a small negative relation with educational outcomes, but more so at the secondary and university educational levels than for elementary pupils. More recently, the meta-analysis of Amez et Baert (2020) showed a negative association between smartphone use and academic success. For all three meta-analyses, it is unclear whether the association reflects a detrimental effect of smartphone or Internet use on academic performance in adolescents – a position adopted by a number of authors – or a protective effect of better education against problematic online behavior. Data regarding PIU with respect to education are mostly lacking at the adult level. Overall, a negative association could be expected between educational attainment and PIU scores in adults.

1.3.4 Income level

Lastly, income level also appears to be correlated with PIU, but there is no consensus on the direction of the correlation. On the one hand, Kuss et al. (2014) showed that higher PIU was associated with higher income levels, perhaps due to easier Internet access and more intensive online activities for individuals with a higher outcome; on the other hand, Mei et al. (2016), Lai et Kwan (2017) and Schneider et al. (2017) showed that a high income was associated with lower PIU, suggesting that high income could act as a protective factor, possibly due to its association with other variables such as higher social support. Overall, an association between income and PIU can be expected, but there is little reason to predict a particular direction for this association.

1.4 Psychological correlates of PIU

As highlighted in the I-PACE model (Brand et al., 2019; Brand et al., 2016), psychological traits have also been shown by the literature to be related to problematic behaviors in the context of online activities. In the current study, we particularly focused on fear of missing out, anxiety and flow.

1.4.1 Fear of Missing Out

Fear of Missing Out (FoMO: Przybylski et al., 2013) is the pervasive apprehension in an individual that others have rewarding experiences from which one is absent. It has also been defined as the persistent desire to stay connected with people in one's social network (Elhai et al., 2021). The phenomenon of FoMO can be understood as self-created uncertainty, resulting from chronic or situational deficits in the satisfaction of psychological needs. Several studies have found that FoMO was significantly associated with PIU, either on its own (see Elhai, Dvorak, et al., 2017; Elhai, Gallinari, et al., 2020; Elhai et al., 2016; Wolniewicz et al., 2018 for example), or as a mediator of the relation between depression/anxiety and problematic smartphone use (Elhai, Dvorak, et al., 2017; Elhai et al., 2016; Elhai, Yang, et al., 2020; Elhai et al., 2021), or problematic use of online videogames (See Li et al., 2021; Wang et al., 2022; Yuan et al., 2021 for example). Counterintuitively, FoMO appeared more related with the "process use" of smartphone (i.e. news consumption, entertainment, and relaxation) than with its "social use" (social media activities, massive multiplayer online game; see (Elhai, Gallinari, et al., 2020; Elhai, Hall, et al., 2017). Overall, a high FoMO score should be positively associated with PIU scores in general, possibly with a stronger association for activities related to non-social use of Internet.

1.4.2 State anxiety and trait anxiety

Anxiety is a normal reaction to a stressor, helping the individual develop a "fight or flight" response to a stressful experience; but this response can also be excessive and lead to cognitive and behavioral difficulties (Fish et al., 2014). The concept of anxiety encompasses trait anxiety, which refers to the predisposition to experience states of fear (nervousness, discomfort...) in the presence of a stimulus, and state anxiety, which refers to the transient state of fear in a given situation; these two aspects of anxiety have not always been examined separately in the literature. Recent studies have found that PIU was related to anxiety (Davey et al., 2020), including both trait anxiety (see Davey et al., 2020; Elhai, Gallinari, et al., 2020; Hetzel-Riggin & Pritchard, 2011; Kim et al., 2015 for example) and state anxiety (see Davey et al., 2020; Elhai, Gallinari, et al., 2020; Hetzel-Riggin & Pritchard, 2011; Kim et al., 2015 for example). In particular, a number of studies have shown a correlation between trait or state anxiety and problematic use of social networks (see Elhai, Dvorak, et al., 2017; Primack et al., 2017; Thorisdottir et al., 2020 for example), which seems to depend on patterns of use: passive use (scrolling) of a social network is associated with more anxiety than active use (posting ; Thorisdottir et al., 2019). Other studies showed a relation between state anxiety and problematic use of videogames (King et al., 2011; Loton et al., 2016; Mentzoni et al., 2011). The direction of causality is unclear, but one possibility is that Internet use serves as a strategy to cope with anxiety (see Hetzel-Riggin & Pritchard, 2011; Loton et al., 2016). Based on prior literature, state anxiety and trait anxiety scores can be expected to positively predict PIU.

1.4.3 Dispositional flow

Flow refers to an intense state of absorption, a deep engagement in the task; flow is pleasurable and pushes individuals to replicate an experience. Flow is mostly accompanied by

positive consequences for individuals, but there is also a "dark side of the Flow" (Csikszentmihalyi, 1990), which pushes individuals to persevere in certain activities with a persisting sense of well-being (Nakamura & Csikszentmihalyi, 2009) without being aware of harmful consequences, such as neglecting relationships with others, ignoring information outside of the activity, overestimating their skills in the activity, etc. Dispositional flow, the predisposition to experience flow easily (Jackson & Eklund, 2002; Jackson et al., 1998), is associated with intensive use of the Internet (Chen et al., 2017; Kim & Davis, 2009; Stavropoulos et al., 2018; Thatcher et al., 2008). Dispositional flow may come with with problem use for some online activities, such as social networks (Li et al., 2020) or online videogames (Khang et al., 2013). It may also act as a moderator for other variables: Khang et al. (2013) showed that dispositional flow mediated the relation between motives for Internet use (e.g. social relationship, past-time, self-presence) and problematic digital behaviors, especially for videogames. Overall, a high dispositional flow could be positively associated with PIU scores, especially for social networks and online videogaming.

1.5 Limitations of prior literature

The literature has shown relations between PIU and a substantial number of socio-demographic variables and psychological traits. Overall, PIU seems to be higher in young adults and in individuals with low academic achievement, in men or women depending on the type of activity, and possibly for individuals for lower or higher income depending on studies. Higher fear of missing out, higher anxiety and higher dispositional flow all seem to come with more PIU. This complex picture leaves two major questions open, which are the focus of the present study.

First, the predictors of PIU have almost always been studied separately. The sheer number of possible predictors included in frameworks such as the I-PACE model (Brand et al., 2016) – makes it difficult to disentangle their separate contributions and their relative weights in

determining problem uses. Many of these predictors could be overlapping: for example, FoMO is a form of anxiety, sex and age are both related to anxiety, income is related to age, FoMO may depend on age, and so on. Prior to any meaningful effort to accurately model predictors of PIU and as a prerequisite to developing effective interventions to limit PIU, it would be necessary to test the major predictors simultaneously to determine their *unique* contributions to problem uses.

Second, a growing literature has demonstrated that PIU is intrinsically related to patterns of Internet use: for example, Starcevic et Billieux (2017) proposed that PIU was linked to specific behaviors, mediated by the nature of Internet activities. Likewise, Kim et al. (2020) showed that the type of online activity was a critical factor in eliciting PIU. Many of the determinants discussed in the prior sections seem to have partly different effects for different activities. Moreover, the specificity of many internet activities raises important questions about the stability of PIU determinants across activities: different profiles of users engage in shopping, streaming or gambling online, and the psychological and socio-demographic correlates of a dysregulated use can be expected to differ. A few studies have shown that the association between socio-demographic predictors and PIU may differ depending on activities (see Dany et al., 2016; Durkee et al., 2012 for example), especially in the case of sex (e.g. Anderson et al., 2017; Demirer & Bozoglan, 2016; Kuss et al., 2014; Müller et al., 2016), but this has not been examined for most variables and especially not for psychological traits.

1.6 Rationale for the present study

1.6.1 Research objectives and hypotheses

According to the I-PACE model (Brand et al., 2019; Brand et al., 2016), PIU result from psychological factors that can interact with situational aspects to trigger (media-)specific behaviors. Prior literature has also demonstrated that problematic online behaviors are rooted in

patterns of Internet use which depend on socio-demographic determinants. As a result, PIU can be expected to depend both on psychological traits, and on socio-demographic variables. In this context, two major questions have been left unanswered by prior literature.

The first question is the relative weight of different predictors of PIU. In particular, it is unclear whether psychological or socio-demographic variables are better predictors of PIU, as these determinants have been typically examined in the context of different research traditions (e.g. sociology vs. psychology). Psychological variables may be more proximal determinants of cognitive and affective responses, but socio-demographic variables may be more strongly related to the specific online behaviors that can degenerate into problematic use. Our first objective was therefore to measure the predictors listed here concurrently and test their relative effects in a multiple regression approach.

The second question is whether the association between a person's characteristics and PIU depend on the type of internet-based activities (videogame, shopping, cybersex, social media, news, streaming, or gambling). This has been demonstrated in some cases, such as problematic cybersex where men are more represented, but the possibility of different relations depending on the type of activities has not been examined for most variables and especially not for psychological traits. Our second objective was therefore to study predictors of PIU across different types of activities, to determine whether the same correlates of PIU mattered independently of patterns of Internet use.

1.6.2 Study design

Our study used an online survey assessing PIU along with possible predictors. The data were collected with two constraints: the sample needed to be large enough to observe small relationships and test many predictors concurrently, and it needed to be representative of the

country population to allow for generalizable conclusions. To these ends, the sample was collected through a polling agency using a quota-based sampling method, with a goal of at least 1500 participants.

To assess possible predictors of PIU, the survey asked questions about socio-economic variables: age, sex, educational attainment, income level. The survey also included scales assessing several psychological characteristics thought to be related to PIU: FoMO, state anxiety, trait anxiety, and dispositional flow. To assess whether the effect of these predictors differed depending on the type of online behavior, measures of PIU were collected both in general, and for a variety of online activities: videogames, shopping, cybersex, social media, news, streaming, and gambling. The data were analyzed using multiple regressions so as to estimate to what extent socio-demographic and psychological variables explained unique variance in PIU across the various types of online activities.

2. Method

Data used in this article are drawn from an online survey conducted in July 2020 among 1504 individuals representative of the French population. The online survey was managed by a professional agency, and respondents benefited from non-systematic incentives.

2.1. Participants

Our sample comprised 1504 Internet users (752 male and 752 female) representative of the French population in terms of age, sex, socio-professional category and region of residence. Representativity of the general population was ensured based on quota sampling. Participants were asked about their sex, age, education (from 1 = "no degree" to 9 = "doctoral degree"), income per household (thirteen responses categories from 1 = "less than 750 euros" to 13 = "more than 7000

euros"), household size, quality of internet connection (on a scale from 1 to 5), whether they had a computer with an internet connection at home (96.5% of the sample did), and whether they had a smartphone with internet access (87.9% of the sample did). Table 1 displays the main socio-demographic characteristics of participants. Although quota-based data collection was conducted to ensure the sample was representative of the French population in general, the composition of the sample also appeared broadly consistent with censuses of the more specific population of French Internet users¹. No participants were excluded from the sample.

Table 1

Demographic information for the sample

Variable	N	Mean	Standard deviation	Range	Skewness	Kurtosis
Age	1504	45.40	17.40	15 – 89	-0.05	-1.15
Education (years)	1496	13.20	3.07	5 – 20	-0.37	0.83
Income (euros)	1392	2758	1485	600 – 8000	1.01	1.35
Number in household	1504	2.62	1.41	1 – 12	1.05	1.82
Internet connection	1451	4.08	0.83	1 – 5	-0.85	0.85

Note. To make this table more legible, education and income were recoded in terms of years and euros by taking the center of each response category.

2.2. Materials

In addition to querying demographics (sex, age, educational attainment and income), participants were asked to complete the following measures.

2.2.1. Compulsive Internet Use Scale (CIUS 5)

We chose to measure PIU with the CIUS (Meerkerk et al., 2008), which is simultaneously one of the most widely cited measures of PIU (Laconi et al., 2014), and a measure with items general enough to be suitable for various types of activities. For the purposes of this study and to

¹ Such as the sample collected by the ARCEP: see https://www.arcep.fr/uploads/tx_gspublication/rapport-barometre-numerique-edition-2021.pdf

limit the length of the questionnaire, we chose to use the 5-item version of the CIUS, using the translation of Khazaal et al. (2012) which has demonstrated good psychometric properties. The five items of this scale use a 5-point Likert scale ranging from (1) "never" to (5) "very often" (e.g. item 1: "*In the past week, how often have you been concerned with each of the following? I find it difficult to stop using the internet while I am online*"), yielding a score between 5 and 25. Internal consistency for this scale was good (Cronbach's $\alpha = .85$).

Participants were also asked to indicate the activity or activities they had most conducted on the internet during the past week, among the seven possibilities investigated in the current study: videogames, shopping, cybersex, social media, news, streaming, and gambling. These activities were chosen because they were both the most consulted websites and applications (except for Wikipedia, which is the only encyclopedia of its category and which was not expected to yield substantial PIU), and the most studied in the literature. Participants could choose up to three activities. For each of their choices, they completed the CIUS5 again with the words "the internet" replaced by the activity under consideration. Participants could also report the website on which they conducted this activity the most, but the corresponding data are not analyzed in detail here.

2.2.2. Dispositional Flow Scale (DFS)

We used the consensual Dispositional Flow Scale (DFS) of Jackson et Eklund (2002), which we translated using a translation-back-translation procedure (van Widenfelt et al., 2005). The nine items of the DFS assess the nine conceptual dimensions of flow (Jackson & Csikszentmihalyi, 1999). We also added an item more broadly measuring core flow to capture the experiential essence of flow (Martin & Jackson, 2008). All items are rated on a 5-point Likert scale ranging from 1 "never" to 5 "always" (e.g. item 2: "*when surfing the web...I do things*

spontaneously and automatically without having to think about it"), yielding a score between 10 and 50. Internal consistency for this scale was acceptable ($\alpha = .78$).

2.2.3. Trait anxiety scale (HEXACO Revised Personality Inventory – emotionality)

Trait anxiety was assessed with 4 anxiety items present in the emotionality facet of Lee et Ashton (2004) HEXACO Revised Personality Inventory. Two items assess the usual presence of anxiety, and two items assess the usual absence of anxiety and are reverse-coded. All items are rated on a 5-point Likert scale ranging from 1 "strongly disagree" to 5 "strongly agree" (e.g. item 11 "*Sometimes I can't help but worry about unimportant incidents*"), yielding a score between 4 and 20. Internal consistency for this scale was below the acceptable threshold ($\alpha = .64$).

2.2.4. State anxiety scale (State-Trait Anxiety Inventory - STAI)

State anxiety was assessed with 20 items of the classic State-Trait Anxiety Inventory (STAI) by Spielberger (1988), translated into French by Gauthier et Bouchard (1993). Half of the items assess the presence of anxiety (items 3, 4, 6, 7, 9, 12, 13, 14, 17, 18), and half of the items assess the absence of anxiety (items 1, 2, 5, 8, 10, 11, 15, 16, 19, 20) and are reverse-coded. All items are rated on a 4-point Likert scale ranging from 1 "no" to 4 "yes" (e.g. item 9 "*I feel scared*"). Possible anxiety scores thus range between 20 and 80. Internal consistency was excellent ($\alpha = .94$).

2.2.5. Fear of Missing Out Scale

In the reference publication on FoMO, Przybylski et al. (2013) proposed 10 items to measure this construct. All items are rated on a Likert scale ranging from 1 "Doesn't fit me at all" to 5 "Fits me perfectly" (e.g. Item 7: "*It bothers me when I miss an opportunity to meet my friends*"), yielding a total score between 10 and 50. As there is no psychometric validation of this scale in

French, we translated the scale using a translation-back-translation procedure (van Widenfelt et al., 2005); internal consistency was excellent ($\alpha = .89$).

2.3. Procedure

Participants were recruited by a survey agency between July 9 and July 16, 2020. They received non-systematic incentives for participation (i.e. some participants randomly received a monetary reward). The survey agency recruited participants online; while this leads to over-representation of participants familiar with Internet activities in the sample, this was desirable in the present case because it allowed access to a population of Internet users who, unlike non-users, may suffer from PIU. Informed consent was obtained from each participant prior to participation. The study was performed in line with the principles of the Declaration of Helsinki; the approval of an ethics committee is not required for this type of study under local regulations. Participants answered a few questions regarding demographic information, then completed all scales in order (CIUS-5, DFS, HEXACO, STAI and FoMO).

3. Results

Descriptive statistics for all measures are displayed in Table 2. Overall, most measures had satisfying range with a distribution close to normal. Measures of problematic uses had a mild positive skew, indicating that lower scores were more frequent than higher scores. The exception were the measures of problematic uses for the News and Shopping activities, which had substantial skewness – reflecting the fact that most participants who declared preferentially engaging in these activities in the past week had problematic use scores very close to zero. Using generalized models to account for the non-normal distribution of these two variables did not substantially change the results; these analyses are not reported here.

Bivariate correlations between possible predictors of problematic uses and CIUS5 scores in each activity are summarized in Table 3. As with all other analyses, these correlations were computed based on all available data, which means sample size varied across measures. Most variables had significant correlations with problematic Internet uses, with the largest correlations appearing for age and FoMO.

The choice of a given activity as "most performed during the last week", and thus selected for PIU measurement, was itself dependent on psychological and especially socio-demographic variables. These associations were not directly relevant to our hypotheses, but they can serve to show that the variables functioned as expected (for example, age had a strong negative association with engaging in streaming, $\beta = -.90$, females were much less likely to engage in cybersex, $\beta = -.81$, and education was positively related to consulting the news, $\beta = .33$). The results are detailed in Appendix 1 for interested readers.

3.1. Prediction of problematic Internet use

We used multiple regressions to examine the contribution of each predictor of PIU. The four psychological measures were included as predictors of interest (DFS for Dispositional Flow, HEXACO for trait anxiety, STAI for state anxiety and FoMO for Fear of missing out), as well as socio-demographic variables (sex, age, education, and level of income). The analyses were performed separately for the general CIUS5 score and the scores in each activity; this served both to test whether some predictors differed depending on activity, and to use the separate activity domains as a form of cross-validation (i.e. ensuring that the results were stable for different activities reported by different participants). Each analysis used all available data; the largest sample size was for the CIUS5 score ($n = 1391$, with 112 participants removed due to missing

income data; conducting the multiple regressions without income as a predictor in order to include the whole sample did not change the results).

The results of these analyses are summarized in Table 4. Overall, socio-demographic variables had limited or no relations with PIU. Sex, education, and income level had no meaningful effects on PIU when controlling for other variables. Age had a slight negative effect on PIU in four out of eight analyses (with up to 4.8% of explained variance based on R^2), but these effects were not stable across activities.

Conversely, state anxiety (STAI) and fear of missing out (FoMO) were significant predictors of problematic use scores in all activities. FoMO in particular had large effect sizes, with R^2 indicating that it explained between 13% (general problematic uses score) and 36% (cybersex problematic uses score) of variance in problematic uses, with a higher fear of missing out being associated with more problematic uses. State anxiety was also a significant predictor in all cases, but with much lower effect sizes, between 2% and 12% of explained variance. Higher levels of dispositional flow and lower levels of trait anxiety were associated with less problematic uses in some cases, but the effects were both unstable and very weak between 1% and 2% of explained variance.

The effect sizes for STAI and especially FoMO (with bivariate correlations and beta coefficients up to .60-.65) were surprisingly large for this type of study, suggesting a potential issue of overlap between items of the FoMO scale and items of the CIUS5 scale. To ensure that this was not the case, we conducted a complementary analysis testing the relation between the various predictors and problematic Internet uses, separately for the five items of the general CIUS5 scale. The results are summarized in Table 5 and confirmed that the effects of STAI and FoMO were comparable across items; both were significant predictors of problematic internet use as

measured with all five items (although with lower effect sizes than for total scores, as expected given the low reliability of individual items).

3.2. Comparison of problematic Internet uses between activities

Although this was not a core objective of the current study, it may be interesting for exploratory purposes to compare the extent of PIU between different online activities, as this question is relevant and can be answered based on the present dataset but has received very little attention from the literature. Due to the unusual structure of the data (problematic use scores were available for up to three activities per subject out of seven, creating a situation with both non-independence between measures and missing data by design), problematic use scores were compared using mixed models including a main effect of activity and a random intercept by subject (package lme4 in R: see Bates et al., 2015).

A model taking into account the type of activity ($BIC = 18963$) fit significantly better than a constrained model not taking into account the type of activity ($BIC = 19411$), $\chi^2(6) = 497.05$, $p < .001$, confirming that there was a significant difference in the extent of problematic uses between the various activities. Decomposing the results showed that the lowest level of problematic uses was obtained for the News activity; Shopping was significantly higher, $p < .001$; Social media, Videogames and Gambling were significantly higher than shopping, $p < .001$, but not significantly different from each other, all $ps > .20$; Streaming and Cybersex were significantly higher than all three, $p < .001$, but not different from each other, $p = .763$.

Table 2

Descriptive statistics for all measures

Variable	N	Mean	Standard deviation	Range	Skewness	Kurtosis
DFS (dispositional flow)	1504	34.27	5.69	10 – 50	-0.45	1.51
HEXACO (trait anxiety)	1504	13.11	3.23	4 – 20	-0.13	-0.10
STAI (state anxiety)	1504	42.81	11.5	20 – 80	0.17	-0.20
FoMO (fear of missing out)	1504	20.89	8.42	10 – 50	0.80	-0.20
CIUS5 (general)	1504	11.63	4.84	5 – 25	0.71	-0.10
CIUS5 (news)	821	7.17	3.70	5 – 25	2.31	5.16
CIUS5 (social media)	819	10.43	4.95	5 – 25	0.88	0.02
CIUS5 (shopping)	707	8.01	4.18	5 – 25	1.83	3.19
CIUS5 (streaming)	473	11.66	5.13	5 – 25	0.55	-0.58
CIUS5 (videogames)	443	10.80	4.87	5 – 25	0.76	0.04
CIUS5 (gambling)	119	10.44	5.55	5 – 25	0.76	-0.52
CIUS5 (cybersex)	53	11.47	5.77	5 – 25	0.59	-0.93

Note. DFS = Dispositional Flow Scale, STAI = State and Trait Anxiety Inventory, FoMO = Fear of Missing Out, CIUS5 = Compulsive Internet Use Scale.

Table 3

Bivariate correlations between problematic uses of Internet and their predictors

Variable	CIUS5 general n=1504	CIUS5 news n=821	CIUS5 social media n=819	CIUS5 shopping n=707	CIUS5 streaming n=473	CIUS5 videogames n=443	CIUS5 gambling n=119	CIUS5 cybersex n=53
Sex	.09	-.02	.03	.07	.06	-.07	.13	.24
Age	-.38	-.24	-.35	-.20	-.33	-.19	-.45	-.07
Education	.06	.10	.06	.08	.11	.10	.33	.00
Income	-.05	-.02	-.03	-.01	-.07	-.04	.09	-.04
DFS	.13	.11	.12	.10	.08	.12	.11	.23
HEXACO	.17	-.02	.13	.05	.14	.00	-.02	-.03
STAI	.34	.19	.25	.22	.35	.22	.35	.29
FoMO	.51	.55	.51	.47	.54	.46	.65	.48

Note. DFS = Dispositional Flow Scale, STAI = State and Trait Anxiety Inventory, FoMO = Fear of Missing Out, CIUS5 = Compulsive Internet Use Scale. Sex was coded as 0 = male, 1 = female. Significant correlations are in boldface.

Table 4

Multiple regression results for problematic uses of Internet in all activities

Variable	CIUS5 general n=1391	CIUS5 news n=788	CIUS5 social media n=749	CIUS5 shopping n=679	CIUS5 streaming n=417	CIUS5 videogames n=390	CIUS5 gambling n=115	CIUS5 cybersex n=51
Sex	.02	-.04	-.01	.05	.02	-.04	.03	.03
Age	-.21***	-.08*	.22***	-.06	-.19***	-.03	-.10	.25
Education	.06*	.02	.04	.06	.03	-.04	.04	.06
Income	-.04	.04	.00	.01	.03	.01	.19*	-.25
DFS	.12***	.05	.08*	.09**	.06	.09*	.10	.17
HEXACO	.00	-.14***	-.01	-.10*	-.07	-.11*	-.12	-.08
STAI	.24***	.15***	.14***	.19***	.26***	.20***	.20*	.34*
FoMO	.36***	.49***	.40***	.41***	.40***	.40***	.50***	.60***
95% CI	+/- .05	+/- .07	+/- .07	+/- .07	+/- .09	+/- .10	+/- .16	+/- .28
Total R ²	.36	.33	.32	.26	.37	.25	.52	.42

Note. DFS = Dispositional Flow Scale, STAI = State and Trait Anxiety Inventory, FoMO = Fear of Missing Out, CIUS5 = Compulsive Internet Use Scale. Sex was coded as 0 = male, 1 = female. The table displays standardized estimates. 95% CI is the approximate margin of error to obtain the 95% confidence interval for a given beta coefficient: for example, the effect of sex on general scores on the CIUS5 was .02 with a 95% confidence interval [-.03, .07]. Significant predictors are in boldface. * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 5

Multiple regression results for the five items of the general CIUS5

Variable	Item 1 - Stop	Item 2 - Others	Item 3 - Sleep	Item 4 - Neglect	Item 5 - Morale
Sex	.06*	-.03	-.03	.02	.06*
Age	-.14***	-.16***	-.17***	-.15***	-.22***
Education	.00	-.07**	-.02	-.02	-.04
Income	.05	.14***	.02	.00	.01
DFS	.10***	.04	.09***	.09***	.15***
HEXACO	.07*	-.02	-.06*	-.10**	.09**
STAI	.12***	.16***	.25***	.22***	.19***
FoMO	.20***	.32***	.29***	.33***	.27***
Total R ²	.15	.21	.24	.25	.30

Note. DFS = Dispositional Flow Scale, STAI = State and Trait Anxiety Inventory, FoMO = Fear of Missing Out. Item 1 = having difficulty to stop using the Internet, Item 2 = being told by significant others to use the Internet less, Item 3 = lacking sleep due to Internet use, Item 4 = neglecting daily duties because of Internet use, Item 5 = using the Internet when having low morale. Sex was coded as 0 = male, 1 = female. The table displays standardized estimates. Significant predictors are in boldface. * $p < .05$, ** $p < .01$, *** $p < .001$.

4. Discussion and conclusion

The purpose of this cross-sectional study was to investigate the unique predictive contributions of socio-demographic and psychological predictors of PIU, across various types of online activities. The results revealed that the set of predictors considered in this study were consistently able to predict PIU, with 26% to 52% of total explained variance depending on type of activity. However, socio-demographic and psychological variables were not all equally able to predict problematic uses, with much larger effects for psychological variables. We believe the fact that this study was based on a representative sample of the country population, and that the dataset was of sufficient size to obtain stable estimates of effect sizes for most types of online activities (e.g. the 95% confidence interval for the effect of FoMO on general CIUS scores was [0.31, 0.41], and the confidence interval for the effect of STAI was [0.19, 0.29]), afford a high degree of confidence in these results.

4.1 Socio-demographic and psychological predictors of PIU

Contrary to our expectations, socio-demographic variables only had very limited predictive power for PIU. Educational attainment and income had no stable effects on PIU across online activities. The effect of sex was very small, limited to general PIU scores, and disappeared when controlling for other variables, suggesting that prior results in the literature (e.g. Anderson et al., 2017; Demirer & Bozoglan, 2016; Kuss et al., 2014; Müller et al., 2016) were either driven by confounding variables, or limited to certain samples such as adolescents (Gentina & Rowe, 2020). Age had substantial relations with PIU when considered alone in bivariate correlations, with younger people exhibiting more PIU, in line with the results of Yu et Sussman (2020); however, the effects of age became negligible when controlling for other variables, suggesting that this was largely due to other confounding variables such as differences in use patterns. In a multiple

regression, age only explained a small amount of PIU variance – with beta coefficients between -.08 and .22 – in general PIU and PIU for news, streaming, and social media. Surprisingly, older adults appeared marginally more vulnerable to PIU for social media.

Although we had not anticipated this result, the limited predictive power of socio-demographic variables in PIU can be seen as broadly compatible with the I-PACE model of internet-use disorders. In this framework, socio-demographic variables can be taken to directly influence specific internet-use behaviors, without a causal influence on the affective and cognitive responses (such as craving) which are thought to lead to the emergence of PIU. In other words, the small relations observed between socio-demographic variables and PIU may be interpreted as reflecting only differences in patterns of use, not core differences in cognitive and affective processes leading to problematic use. For instance, age was negatively associated with PIU for streaming and video games, but this can reflect the lower tendency of older adults to engage in these online activities, rather than a difference in the way older adults experience affective responses to streaming or video gaming.

By contrast, the results showed a striking unique contribution of psychological variables and especially FoMO. Consistent with previous works, we found a strong positive association between FoMO and PIU (Elhai, Gallinari, et al., 2020; Elhai et al., 2016; Oberst et al., 2017; Wolniewicz et al., 2018), with beta coefficients up to $\beta = .60$. This was true regardless of the activity considered, in contrast with prior studies (Elhai, Gallinari, et al., 2020; Elhai, Hall, et al., 2017) finding that FoMO was more correlated with "process use" (news, entertainment, relaxation) than with "social use" (social media, online game video games) of the Internet. Surprisingly, FoMO retained by far the best explanatory power in the multiple regression controlling for trait and state anxiety, despite fear of missing out representing a form of anxiety. In our opinion, this is

due to the fact that the FoMO construct does not only capture social anxiety, but also the satisfaction of basic psychological needs such as social relatedness (Deci & Ryan, 2000). This should be tested in future studies.

The importance of FoMO in our study could also be related to the way internet services are currently designed, and in particular, to the fact that websites use more and more "dark patterns": interfaces designed to deceive or manipulate the user (Gray et al., 2018). Dark patterns aim to maximize the profits of platforms by keeping the user engaged as long as possible, locking their usage inside the platform or an ecosystem of services. Alutaybi et al. (2019) postulated that some dark patterns play on the activation of a FoMO state, allowing to maintain the users in a dysregulated use of their services (e.g. "celebrating a new season of content on videogames with our friends"). Individuals predisposed to experiencing FoMO could be more sensitive to these dark patterns and consequently, more at risk of developing problematic uses. Further studies are needed to understand the strong weight of FoMO in PIU and how they relate to the design of online activities.

The second most important association was found between PIU and anxiety. Although effect sizes were much lower than for FoMO, there were consistent associations between state anxiety and PIU for all the types of online activities. This result confirms the link between anxiety and PIU highlighted in a recent review (Elhai, Dvorak, et al., 2017) and study (Elhai, Gallinari, et al., 2020). Part of the role of state anxiety in predicting PIU may have been due to individuals implementing maladaptive coping strategies to manage their anxiety (Elhai, Gallinari, et al., 2020; Kuss et al., 2014; Latikka et al., 2022). The notion of coping refers to all cognitive and behavioral efforts aimed at regulating internal or external demands that threaten or exceed an individual's resources (Lazarus & Folkman, 1984). A maladaptive regulation of psychological stress in

individuals can result in a dysfunctional coping mechanism aimed essentially at escaping from difficulties (Baggio et al., 2018; Gioia et al., 2021): difficulties in reducing anxiety lead to distraction or social diversion aimed essentially at avoiding negative affect at all costs (Mariage & Schmitt-Fourrier, 2006). An extensive Internet use could satisfy this form of escapism by helping manage negative emotions (Gioia et al., 2021; Kardefelt-Winther, 2014). This dysfunctional strategy has been widely described in problematic uses of online video games, online gambling social media and the Internet use in general. (Flayelle et al., 2019). Compatible with this possibility, correlations between PIU and state anxiety were somewhat higher for activities creating a high level of attentional distraction, especially cybersex and streaming, and to a lesser degree videogames and gambling. Further studies are needed to confirm this.

By contrast, PIU had a negligible relation with our measure of trait anxiety, even without controlling for other predictors (Table 3). There is no obvious explanation for this finding. It might be the case that use of the Internet to manage negative emotions is not stable in an individual, driving a stronger relation with state anxiety than with trait anxiety; but it is also very possible that this is due to the very short trait anxiety measure with poor psychometric properties used in the current study (four items of the HEXACO with $\alpha = .64$). Given the substantial relation between PIU and state anxiety for all activities, it would be worth exploring the role of trait anxiety in more detail in future studies with a longer and more reliable scale.

Lastly, we found a slight association between dispositional flow and PIU: individuals with a tendency to experience more flow had more PIU, in line with prior results (Khang et al., 2013; Kim & Davis, 2009; Stavropoulos et al., 2018). This is compatible with what Csikszentmihalyi (1990) called a "dark side of the flow": individuals experiencing cognitive absorption and a deep commitment to persisting in certain activities, without realizing the harmful consequences of these

behaviors on their daily lives. However, the association between flow and PIU was very weak (with the highest $\beta = .11$) and only existed for general scores, social media, videogames and shopping activities, suggesting that flow is not a major determinant of problematic use.

In sum, psychological traits – and more specifically anxiety and FoMO – appeared to play a key role in developing PIU, as suggested by Brand et al. (2016). Critically, and contrary to our expectations based on prior literature, psychological traits were more important predictors of PIU than all socio-demographic variables. These results represent a major contribution to our understanding of Internet-specific addictive behaviors, as well as to what distinguishes the etiology of problematic online behavior versus non-online behavior.

Our findings also challenge the conclusions of some recent studies on the impact of digital use on well-being. Beyond the first level of digital divide (referring to the difference between individuals with and without digital access) and the second level of divide (referring to the difference in individual expertise with the use of digital tools), some economists have argued for the existence of a third level of digital divide (Aubouin, 2022), reflecting inequalities in the outcomes of digital use. This third level of digital divide has been claimed to be largely dependent on socio-economic variables: for example, poorer and younger individuals would be more vulnerable to negative outcomes and would experience a stronger and more negative influence of digital use on their well-being (Pénard et al., 2013). By contrast, our results make it clear that negative outcomes of digital use are not primarily driven by socio-economic variables, but heavily depend on psychological determinants.

4.2. Limitations and Future Directions

A first major caveat of the current study concerns the definition of PIU, and what exactly is reflected in the CIUS 5 measure we used to assess PIU. Problematic uses of the Internet can be

viewed either as a continuum (with higher CIUS 5 scores indicating more problematic use), or as a behavioral disorder constituting a binary variable (problematic vs. non-problematic use). The CIUS 5 does not provide a cut-off score that could be used to diagnose Internet use as pathological (Laconi et al., 2014). Instead, it is designed to measure PIU as a continuum (with scores ranging from 5 to 25: a subject answering 2 out of 5 on the item "I find it difficult to stop using the Internet while online" has a higher PIU score than a subject answering 1 out of 5), and we analyzed the data as such using regressions. In other words, stating that FoMO predicts "higher scores of PIU" does not automatically mean that FoMO predicts a "higher probability of having a behavioral disorder related to dysregulated Internet use", in the sense of functional impairment and tangible negative outcomes at the individual, professional, or personal levels.

Diagnosing the presence of a clinical behavioral disorder related to Internet use is notoriously difficult: it depends on definitions of disorders (Pontes et al., 2022 for example with Internet Game Disorder), on the scale (Laconi et al., 2014), and should include both quantitative and qualitative criteria. As a first approximation, we conducted an exploratory analysis using logistic regression to predict the categorization of individuals as "in the top 2.5% of general PIU scores" or "not in the top 2.5%". The results showed four significant predictors: FoMO, state and trait anxiety, and dispositional flow (all $ps < .01$). This serves to suggest that predictors of having an actual disorder may be the same as predictors of PIU scores even when not at the extreme end on the continuum, and it also confirms that psychological traits are probably the key variables here. However, further studies would be needed to replicate these conclusions based on purposeful categorization of clinical disorders.

Another possible direction for improvement is the measurement of PIU. In line with Starcevic et Billieux (2017), we chose to consider that PIU was linked to specific behaviors

mediated by the nature of Internet activities. Testing PIU for different types of activities was a strength of our current study, allowing to ensure the stability of predictors of PIU across activities; but it may also have come with decreased measurement quality. Our version of the CIUS 5 items adapted to each activity took away from its initial objective and may have provided less precise items. (especially for shopping and news: items such as "neglecting daily duties because of Internet use" are less likely to be endorsed for an activity such as shopping for commodities). Although this was required to make the measure comparable across activities, an alternative would be to use reliable measures of problematic uses tailored to a specific activity. Such measures currently exist only for a few activities, such as social network sites (Bergen Scale: Andreassen et al., 2012).

Lastly, there is room for improvement in our categorization of online activities. As demonstrated by prior studies (Kim et al., 2020) the type of activity is a critical factor in the emergence of PIU. Capitalizing on the fact that people can engage in several activities on the Internet, we asked participants to choose up to three activities so as to capture a broader range of Internet uses. We chose to assess problematic uses in general, and separately for streaming, cybersex, gambling, social media, videogame, news, and shopping. Yet some activities can encompass both social networking and video games (e.g. playing Fortnite and chatting with other players), both social networking and streaming (e.g. looking at a Twitch stream and posting comments), and so on. To overcome this problem, some authors chose to dichotomize process use and social use (Thorisdottir et al., 2019 for example), whereas others chose to focus on a particular platform like Facebook (Rothen et al., 2018 for example).

Regarding internet-based activities, News and Shopping appeared to have especially low PIU scores. It could be due to the fact that these activities inherently come with less problematic uses; they could also be due to the design of the websites or applications used in these activities,

as some designs can elicit more or less PIU due to the presence of dark patterns (Brignull, 2010; Mathur et al., 2019). However, qualitatively examining the websites reported by the participants suggested that these lower scores for News and Shopping had more to do with the fact that participants tended to engage in these activities for purely utilitarian purposes (such as checking daily news and the weather report, buying commodities). This is expected to come with low problematic use scores, given the content of CIUS5 items (e.g. "I find it difficult to stop [activity] while online"). It would be of interest to consider that the PIU criteria for utilitarian activities may be different and could require specific measurement including consultation and/or transaction frequency; or it may be worth specifically excluding these types of activities from measurement.

The solution of focusing on a particular type of activity (or even a particular website or platform) was not suitable for our survey aiming to target all major categories of digital services, but it probably offers the most precision. Therefore, studies zooming in on an activity should be viewed as complementary with our broader results. This will open the possibility of more fine-grained investigations, especially when it comes to platform design. As noted above, FoMO may be triggered by the presence of dark patterns embedded in the design of social media websites (Alutaybi et al., 2019). This raises questions regarding the regulation of digital platforms; we know very little about digital strategies encouraging dark patterns, except that monetizing individual data and individual attention is at the heart of the business models of major platforms (Zuboff, 2019). More investigations are needed to evaluate the relations between business models, dark patterns and PIU. In this light, our study can be viewed as a first step towards public health policies that take into account both the socio-demographic and psychological characteristics of the users to shape prevention policies on PIU by limiting the possible deleterious effects of platform designs.

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Appendix 1

Table A1

Predictors of having a particular activity chosen as "most frequent during the last week"

Variable	news	social media	shopping	streaming	videogames	gambling	cybersex
Sex	-.03	.10	.24***	-.22**	-.17**	-.34**	-.81***
Age	.76***	-.44***	.13*	-.90***	-.61***	.11	-.22
Education	.33***	-.02	.02	.09	-.02	.01	-.03
Income	.13*	-.02	.02	.02	-.01	-.01	-.00
DFS	-.07	.23***	.13*	.17**	.09	.06	.22
HEXACO	.02	.24***	.09	.11	.07	-.32**	-.24
STAI	.06	-.14*	-.09	-.07	-.12	.12	.38*
FoMO	-.20**	.09	-.10	.07	.13	.39***	.23
Number "yes"	821	819	707	473	443	119	53
R ²	.20	.10	.03	.20	.11	.07	.11

Note. The table displays estimates from a logistic regression, with all predictors standardized. Sex was coded as 0 = male, 1 = female. R² values use Nagelkerke's R². Significant predictors are in boldface. * $p < .05$, ** $p < .01$, *** $p < .001$.