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Research protocol for BootStRaP assessment phase: A nine-nation study on boosting societal adaptation and mental health in a rapidly digitalising, post-pandemic Europe[☆,☆☆]

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A R T I C L E I N F O

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A B S T R A C T

Background: There is increasing global concern about the harms associated with problematic usage of the internet (PUI) affecting young people. Various risk factors have been proposed, but there is a scarcity of reliable evidence on the extent of the problem, who is most at risk of developing PUI and why, and how best to tackle it.
Objectives: BootStRaP (ISRCTN59576080) is a five-year multinational research programme designed to boost young people's health and resilience by determining, through prospective longitudinal assessment, the risk factors associated with PUI and its health economic impact and designing and testing preventative self-management interventions tailored to individual risk factors.
Methods: This paper describes the first phase of the project (i.e., Cohort 1). A sample of over 2500 schoolchildren aged 12–16 years was recruited across nine European countries. They were prospectively monitored over a 6-month period using a dedicated smartphone application (*BootstrApp*), through which their internet use habits, health and wellbeing were measured. Young people were involved in the co-design of aspects of the protocol including the recruitment plan and elements of the app design. The components of the assessment battery were chosen to investigate specific individual, clinical, cognitive and environmental risk determinants as defined a priori in an evidence-based logic-model. Participants were assessed using a combination of standardised demographic and clinical questionnaires, ambulatory assessment techniques, cognitive testing and passive digital monitoring. Multimodal data is analysed according to machine learning and structured equation modelling.
Expected outcomes: Our findings will contribute toward A) developing algorithms for predicting individuals at risk for PUI, B) identifying actionable variables for application to subjects as interventions for testing in the second phase of the project, C) validating risk hypotheses stated in the logic model of PUI including the interplay between predisposing risk factors (e.g., impulsivity, compulsivity), affective and cognitive processes (e.g., reward-related attentional biases), and executive functions (e.g., inhibitory control), D) calculating the health economic cost and impact of PUI in young people across Europe.

1. Introduction

1.1. Origins of the BootStRaP project

While the rise of digitalization offers improved access to information, communication, entertainment, and eHealth, there are also emerging risks and challenges. Adolescents, who are early adopters of digital technologies and applications, experience both the positive (e.g., keeping in touch with peer groups) and the negative effects (e.g., challenges in managing the balance between online and offline activities). The relationships between internet use and mental health outcomes are complex. Some studies suggest that frequent internet use may contribute to poor mental health, whereas others report positive associations with well-being, forming a spectrum from controlled/adaptive use to uncontrolled/maladaptive use [1]. The adverse impact may be determined less by the amount of time spent online (e.g., see near zero associations between time spent on social media and well-being; [2]), but more by the underlying motivation, usage patterns, and functional impairment, with addictive patterns being linked to more negative outcomes [1,3–6].

Problematic Usage of the Internet (PUI) refers to maladaptive online behaviours that are characterised by loss of control and harmful usage patterns, and which cause serious consequences for the individual and society [3]. Adolescents with only partly developed cognitive control mechanisms and those with pre-existing mental health conditions are particularly vulnerable to PUI [7,8]. That is, the increased use of the internet to cope with negative emotions, combined with the incomplete development of cognitive control systems, may create a significant risk for PUI. This can manifest in excessive gaming or gambling, which are recognised as disorders due to addictive behaviours in the ICD-11 [9], or other forms of harmful use such as via the use of social media [10]. Depending on the precise thresholds and definitions used, up to 25 % of the population report being affected by some form and degree of PUI with a greater burden for those living in low/lower-middle income countries [11,12]. The COVID-19 pandemic has, at least temporarily, exacerbated these issues, where rates of PUI among European school children were found to reach up to 30 % during that period [13,14], whereas the longstanding impact of the pandemic in fuelling PUI rates across the globe is yet to be understood.

It is important to acknowledge and pinpoint the rise in PUI and its adverse effects on the health and well-being of individuals, especially teenagers [4]. In response to the rising concern over PUI, the European Parliament has initiated the Digital Services Act (DSA) to protect minors from harm on VLOPs (very large online platforms; [15]) and the EU further recommended introduction of community and clinical interventions to facilitate early detection and prevention of PUI. However, reliable evidence is still lacking, and only few evidence-based (preventative) interventions are currently available [16]. To address this, the European Network for Problematic Internet Use (EU-PUI) and its strong citizen stakeholder alliance, called for a coordinated, multinational research initiative to establish standardised methodologies for measuring PUI, identify factors that contribute to risk or resilient outcomes, and develop community-based prevention strategies. This research would involve longitudinal cohort studies and interventional trials [4]. The BootStRaP project responds to this call.

BootStRaP (Boosting Societal Adaptation and Mental Health in a Rapidly Digitalizing, Post-Pandemic Europe) is a five-year multinational citizen-science initiative, funded by the European Health and Digital Executive Agency (HaDEA) under its 2022 Horizon Europe Health programme (Grant Agreement ID 101080238; signed 21/04/2023). This work was supported by UK Research and Innovation program (the University of Cambridge project number: 10077671, the Euro Youth Mental Health project number: 10082693, the University of Hertfordshire project number: 10075008, the University of Southampton project number: 10075760). This work has received funding from the Swiss State Secretariat for Education, Research and Innovation (SERI). BootStRaP's ambition is to leverage multi-stakeholder agreement, and advance health and social policy and practice change to safeguard vulnerable adolescents as a public health research priority [3,4]. The consortium started its work in July 2023.

1.2. BootStRaP logic model

The BootStRaP research plan is based on the hypothesis that PUI can act both as a consequence and causal factor for individual and relational health and well-being issues, including impaired mental health (e.g., mood and anxiety disorders, addiction, suicidal behaviour), physical health (e.g., obesity, eating and sleep disturbances, musculoskeletal issues), family and social interaction (e.g., poor/conflicted relationships), academic and occupational performance (e.g., low exam grades, university dropouts, absenteeism and presenteeism), as well as societal issues such as 'infodemia' (e.g., far-reaching spread of both accurate and inaccurate information about a certain issue), misinformation, conspiracy beliefs, and denial behaviours (e.g., vaccine hesitancy) [3,11,17–19]. Investigating the interaction of these factors over time is necessary to identify causal relationships and risk determinants as a basis for intervention.

Current aetiological models [7,20] suggest multifactorial causative mechanisms are involved in the development and maintenance of PUI, which we have transferred into a broader logic model for the BootStRaP project (see Fig. 1).

Convergent evidence suggests that vulnerability to PUI is linked to a broad range of individual, relational, and societal factors that centre around fundamental difficulties in executive processing linked to self-control, which may feasibly be detected in at-risk individuals. Self-control in relation to internet use can, in turn, be decomposed into (at least) two complementary and potentially interlinked latent phenotypes: **A) affect regulation** (i.e., the (in-)ability to manage and modulate emotional responses, including sensitivity to positive or negative reinforcement to maintain emotional stability), and **B) inhibitory control** (i.e., the (in-)ability to restrain impulsive or compulsive urges to engage repetitively with the internet) [7,20].

PUI driven by low affect regulation capacity may be learned through positive (i.e., experiencing reward and pleasure) and negative (i.e., experiencing less stress and negative mood) reinforcement where the internet is used to "feel better/less bad" (e.g., looking at the Instagram newsfeed to experience fun, searching for health-related information to relieve oneself from health-associated worry). PUI driven by low inhibitory control may be associated with more urge-driven or habitual behaviours that cannot be controlled and persist, possibly in a stereotyped way, despite knowledge that they are unnecessary or in the face of negative consequences, mirroring compulsive disorders such as obsessive-compulsive and related disorders [7,21]. Thus, individuals whose PUI is predominantly driven by compulsive tendencies may experience the feeling that "it must be done/can't be stopped" which might be accompanied by the distressing expectation and experience that it cannot be controlled [20].

As PUI and the associated health issues tend to develop early, and as no evidence-based treatments yet exist [22,23], the case for early detection and intervention to prevent progression to addiction and other forms of ill-health or harm is strong [3,24]. As the determinants of PUI are so varied, preventative interventions tailored to the individual are likely to be more effective than generic approaches [4,19,25]. Self-management interventions applied at scale in the school setting before PUI develops are expected to be less stigmatising and cost-effective [26]. However, health and social policy recommendations for mitigating the emerging risks of PUI require a sound and comprehensive understanding of the causes, effects and associated health economic costs and burdens, which is currently lacking because of methodological inconsistencies in the research base, including reliance on cross-sectional approaches and the use of bias-prone self-report tools [3,4,27].

1.3. BootStRaP aims and objectives

BootStRaP brings together a multidisciplinary consortium to use state-of-the-art digital methods to closely evaluate the internet usage patterns of young people across Europe over time, identify PUI behaviours that risk resulting in harm, and devise strategies to tackle these issues. The project will employ algorithm-based models to create digital screening and assessment platforms. BootStRaP will then develop universal self-management preventative interventions for direct delivery to the individual on a smartphone app, for use at school or at home without need for substantial intervention from teachers. The long-term goal is to develop and test two CBT-informed self-management preventative interventions targeting the two assumed key mechanisms underlying risk for developing PUI (i.e., A) affect regulation and B) inhibitory executive control) for delivery to whole populations of adolescents via digital (smartphone app) technologies. The project is structured in three consecutive cohorts that build on one another. Cohort 1 constitutes the assessment phase and serves as the empirical foundation of the project, addressing non-clinical samples. Its primary objectives are to 1) collect large-scale, multimodal data on adolescents' internet usage patterns, well-being, and related psychological mechanisms across nine European

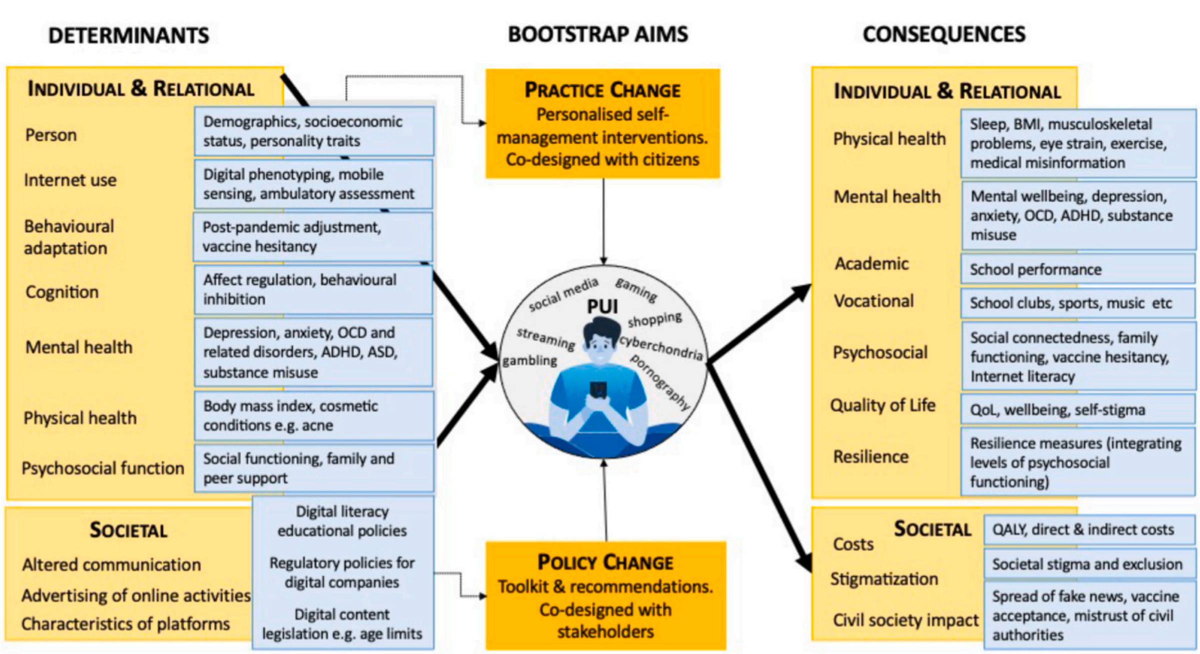

Fig. 1. Addressing the challenges of a rapidly digitalizing society with a focus on PUI: A logic model.
Note. ADHD – Attention-Deficit/Hyperactivity Disorder; ASD – Autism Spectrum Disorder; OCD – Obsessive-Compulsive Disorder; QALY – Quality-Adjusted Life Year; QoL – Quality of Life; PUI – problematic usage of the internet.

countries; 2) use these data to establish a knowledge base on psychological mechanisms underlying PUI and to develop and train a machine-learning algorithm capable of distinguishing high- or low-risk profiles for emerging problematic internet use; and 3) establish the psychometric and technical foundations for the BootStRaP digital assessment platform (the *BootstrApp*, see section 2.3.1). The resulting algorithmic model will inform the allocation and tailoring procedures in Cohorts 2 and 3 (see section 2.1), which aim at developing and testing interventions to prevent PUI in vulnerable populations. Here, we will specifically describe the methodology of Phase 1 "Assessment" while giving a shorter overview of Phase 2 "Intervention" (see Fig. 2).

2. Methods

2.1. Study design

The study design involves three sequential 12-month cohorts of European adolescents, resulting in two study phases covering assessment (Phase 1: Cohort 1) and intervention periods (Phase 2: Cohorts 2 and 3; see Fig. 2). The detailed description and outcomes of Cohort 1, which was prospectively preregistered on 2nd July 2024 (ISRCTN59576080; https://doi.org/10.1186/ISRCTN59576080), are the objectives of this research protocol. Phase 2 (i.e., Cohort 2 and Cohort 3) is given a brief outlook description with a focus on the methodological interconnection of all three cohorts. At the time of revising this manuscript, the recruitment of Cohort 1 (see description below) is completed. Cohort 1 had a recruitment target of 2500+ participants.

2.1.1. Cohort 1

Cohort 1 focuses on assessing the multifactorial determinants of healthy and unhealthy internet use (see Fig. 1 for the Logic Model of PUI). The aim of Cohort 1 is to identify the multifactorial determinants of unhealthy internet use and quantify individual risk for PUI, striving to compute the first algorithms for determining healthy and harmful usage of the internet (see Fig. 2). Further, Phase 1 focuses on developing a digital assessment tool ('*BootstrApp*'), co-created with young people, for the early detection of adolescents at risk, as well as for targeted interventions during Phase 2.

The observational investigation in Cohort 1 includes three assessment points (see Fig. 3): a baseline (i.e., day one) measure (t0), a mid-term assessment three months (i.e., day 85) after baseline (t1), and an endpoint assessment six months (i.e., day 169) after baseline (t2). One month is counted as 28 days. Every assessment has a time window of 4 days and a certain number of reminders to be completed. The last possible day to end the study is day 190.

The t0 and t2 assessments include the same instruments, except for demographic information, which is only collected at t0. The instruments at t0 and t2 specifically involve self-report questionnaires measuring general and specific PUI symptoms; self-report questionnaires on quality of life, well-being, and stigma; self-report questionnaires assessing clinical variables (e.g., obsessive compulsive disorder, depression, anxiety, substance use, and cyberchondria), alongside a cognitive assessment quantifying affect regulation and inhibitory control. For convenience, the assessment is divided into four blocks, each requiring approximately 15 min to complete (see Fig. 3). The blocks must be answered consecutively, but breaks are allowed between and within blocks whereafter participants are directed back to the point where they left off. Participants have four days to complete all four blocks. After this period, they receive reminders about missing questionnaires for 10 days (for t0) or 18 days (for t2). If the instruments remain incomplete after these periods, access to the respective assessment is closed. Such participants do not drop out after t0, but will be invited to the next

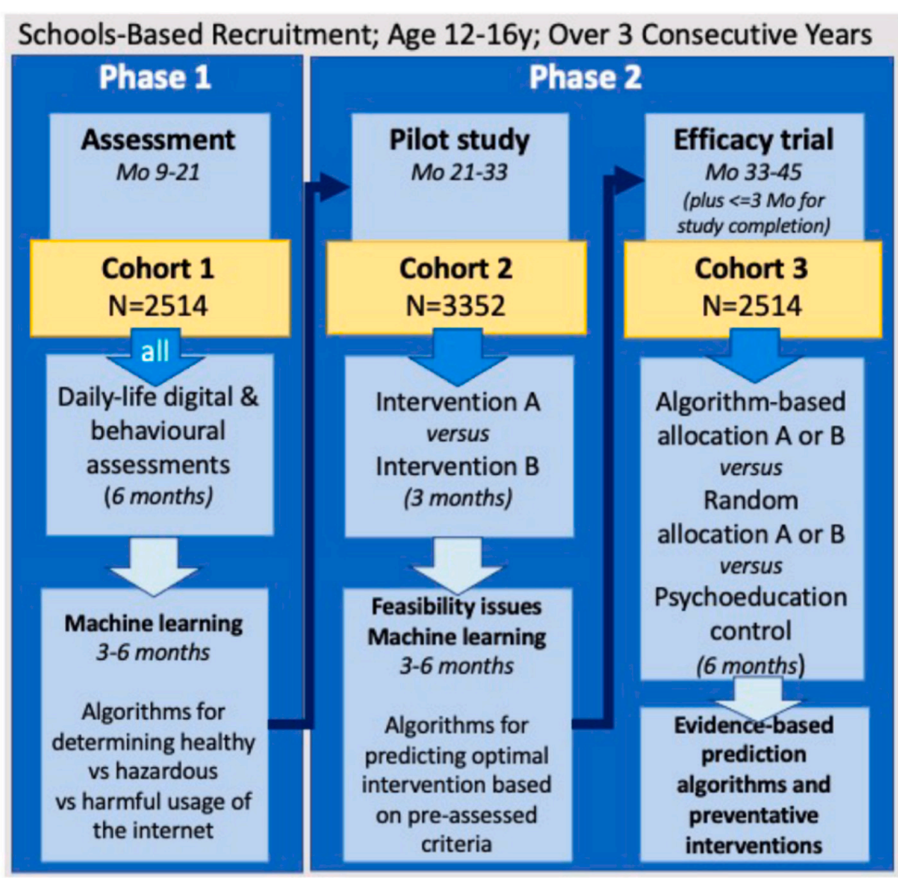

Fig. 2. Assessment and intervention approach and design.
Note. Intervention A = addressing affect regulation; Intervention B = addressing inhibitory control.

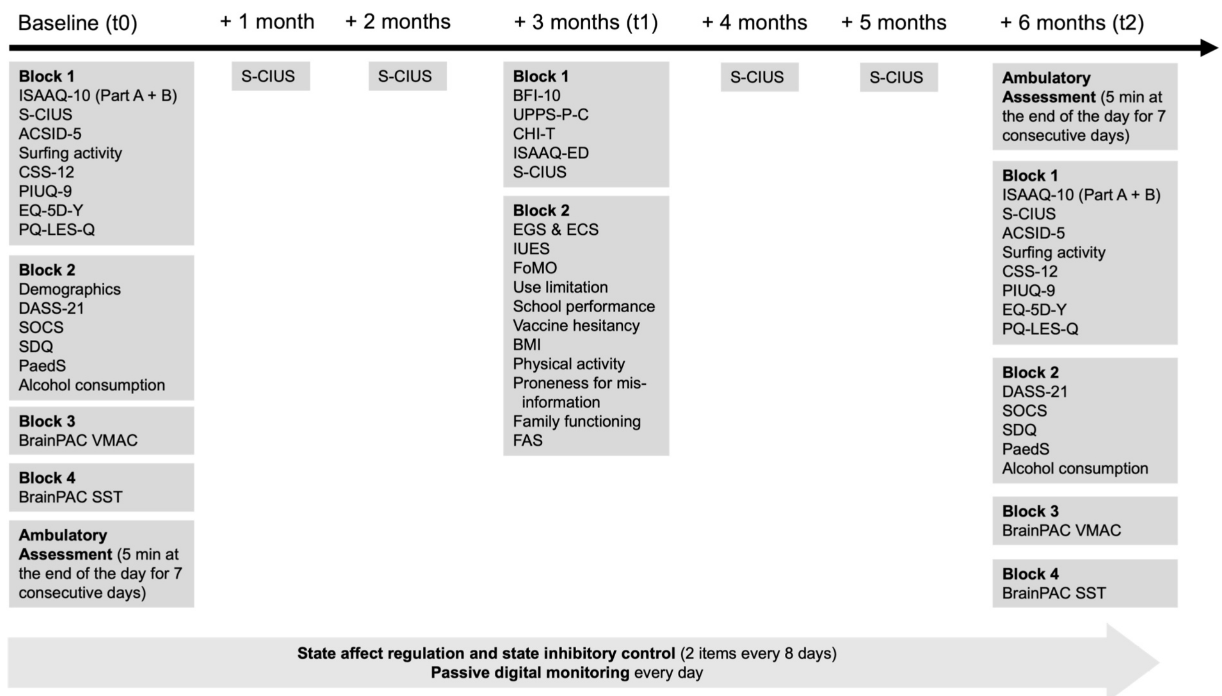

Fig. 3. Assessment workflow for Cohort 1.

Note. The instruments are arranged in the order in which they appear in our survey, unlike the descriptions in the instruments section, where they are organised by category. Please see the instruments section for a complete description of instruments. **ACSID-5** = Assessment of Criteria for Specific Internet-Use Disorders, 5-item version (cf. ACSID-11; [28]); **BFI-10** = Big Five Inventory, 10-item version [29]; **BMI** = Body Mass Index; **BrainPAC SST** = BrainPAC-enhanced Stop Signal Task [30]; **BrainPAC VMAC** = BrainPAC-enhanced value-modulated attentional capture [30]; **CHI-T** = Cambridge–Chicago Compulsivity Trait Scale **[31]**; **CSS-12** = Cyberchondria Severity Scale, 12-item version [32]; **DASS-21** = Depression Anxiety Stress Scale, 21-item version [33]; **ECS** = Experience of Compensation Scale [34]; **EGS** = Experience of Gratification Scale [34]; **EQ-5D-Y** = EuroQol Five Dimensions for Youth [35]; **FAS** = Family Affluence Scale [36]; **FoMO** = Fear of Missing Out Scale [37]; **ISAAQ-10** = Internet Severity and Activities Addiction Questionnaire, 10-item version [38]; **ISAAQ-ED** = Internet Severity and Activities Addiction Questionnaire – Eating Disorders [39]; **IUES** = Internet Use Expectancies Scale [40]; **PaedS** = Paediatric Self-Stigmatization Scale [41]; **PIUQ-9** = Problematic Internet Use Questionnaire, 9-item version [42]; **PQ-LES-Q** = Paediatric Quality of Life Enjoyment and Satisfaction Questionnaire [43]; **S-CIUS** = Short Compulsive Internet Use Scale [44]; **SDQ** = Strengths and Difficulties Questionnaire [45]; **SOCS** = Short Obsessive Compulsive Disorder Screener [46]; **UPPS-P-C** = Urgency – Premeditation - Perseverance - Sensation Seeking - Positive Urgency Scale for children [47].

assessment.

The severity of PUI is additionally assessed monthly (i.e., day 1, day 29, day 57, day 85, day 113, day 141, day 169) with the short version of the Compulsive Internet Use Scale (S-CIUS, (see below) as an ecological measure to inform our machine learning algorithm with a frequent measure of PUI. For the S-CIUS, 10 days of reminders are planned in case participants miss the first invitation.

The measures at t1 focus on persons' latent characteristics (e.g., impulsivity, compulsivity, personality), social and family factors, as well as operant learning mechanisms related to PUI (e.g., experience of reinforcement, use expectancies). The t1 assessment consists of two blocks of self-report questionnaires, each taking approximately 15 min to complete. Both blocks must be answered consecutively within four days. After this period, participants are reminded about missing questionnaires for 24 days, after which access to the t1 assessment is closed. These participants do not drop out but will be invited to the next assessment.

Following t0 and immediately before t2, participants are required to complete a 5-min end of day assessment over seven consecutive days. This assessment captures state variables alongside more stable psychological mechanisms measured in our test battery and enables us to observe fluctuations in mood, stress, temptation, usage of the internet and associated experience of pleasure, relief, and interference with other activities.

To provide additional repeated measures for the machine learning algorithm, two items targeting key constructs related to PUI (i.e., affect regulation and inhibitory control) are continually assessed every eight days throughout the six-month assessment period. Each assessment is announced via a notification and must be completed within a 24-h time window, after which access to that assessment will be closed.

To enhance objectivity and minimise confounds, we integrate continuous passive "digital phenotyping" and mobile sensing to track behavioural patterns [48–51]. Of note, digital phenotyping can be viewed as an umbrella term describing in general the prediction of psychological/psychiatric variables from digital footprints, whereas mobile sensing describes a particular focus on sensing such variables from digital footprints on mobile devices such as a smartphone [52,53]. For details, see 2.3.2.

2.1.2. *Cohort 2*

In Cohort 2, the development of an app-based preventative intervention will be co-created with young people and aims at boosting healthy self-management of internet usage across the range of risk. Two self-management preventative interventions will be delivered via the previously developed *BootstrApp* targeting affect regulation and inhibitory control in comparison to a control group. Allocation to the three groups follows a randomised procedure. The collected data about the psychological mechanisms from Cohort 1 result in a risk-prediction model (see Machine Learning in section 2.6) as a basis for distinguishing participants with low or high risk for PUI. This risk-prediction model is embedded into the *BootstrApp* and allows for an initial evaluation of how risk profiles relate to differential responsiveness to the preventative intervention conditions implemented in Cohort 2. Results of Cohort 2 will be used to identify the key moderating and mediating variables determining responsiveness for the two preventative intervention types (i.e., affect regulation and inhibitory control), from which we train the response-prediction algorithm for enabling personalised intervention allocation in Cohort 3 (dynamic according to individual characteristics) with the greatest chance of success for tailoring the intervention. This research objective will be described separately.

2.1.3. Cohort 3

In Cohort 3, we combine the risk-prediction (Cohort 1; high or low risk) and the response-prediction (Cohort 2; affect regulation or inhibitory control) algorithms to conduct a randomised controlled trial testing the efficacy and cost effectiveness of personalised algorithm-based allocation of self-management interventions. The self-management interventions will be delivered exclusively via the *BootstrApp*. We thus deliver a form of preventative intervention tailored to individual risk and response prediction, measuring PUI symptoms but also secondary outcomes related to quality of life, wellbeing, stigmatization and other social adaptation problems and functional impairment. We use information gained on psychosocial and health economic impact of PUI (derived in Cohort 1) and effectiveness of algorithm-based interventions (Cohort 2, 3) to formulate global policy standards.

2.2. Participants

Recruitment, implementation and retention of study participants for all phases are performed in school settings across 9 European sites (France, Germany, Hungary, Lithuania, Netherlands, Portugal, Spain, Switzerland, United Kingdom).

Recruitment of Cohort 1 was coordinated to start within a four-month period across all centres, which began in mid-December 2024. Phase 1 recruitment, assessment and data collection was completed by the end of October 2025. We recruited adolescents aged 12-16y, representing a stable student population at high risk [24]. To cover a broad, heterogeneous, and diverse population of students, the recruitment was planned in Secondary-, High- and Comprehensive Schools as well as Grammar Schools, and a small proportion represents further Education Colleges. With the recruitment of different schools, spanning from high- to middle- and lower-income countries, as well as the selection of schools in rural and urban areas, we aimed to address a wide range of socio-economic status. Furthermore, we had no exclusion criteria except of age and access to a mobile phone with a required minimum operating system (e.g., no exclusion of certain diagnoses such as ADHD) and we are studying a healthy, non-clinical population. It was also possible to participate in English in countries outside the UK (e.g., students from Ukraine can also take part or people in the schools who had recently moved in). We invited participation from whole school classes, representing sociodemographic distribution within a geographical area. Cohort 1 targeted 2514 participants (Total $N = 8380$ over 3 years for all cohorts [2500–3400 per year]; further descriptive results including the final sample size of Cohort 1 will be reported elsewhere). Both sexes were included, as overall prevalence rates of PUI are similar for males and females, though gender-specific patterns exist. In addition, we addressed gender diversity / variable gender identity. It was possible to distinguish the current gender from the sex at birth, to indicate other gender forms, or to omit the information.

Multiple measures were implemented to mitigate the potential risk of reduced participation or increased drop-out associated with the comprehensive assessment battery. The recruitment relied on a consecutive process of informing and engaging relevant parties including educational government bodies, school authorities and representatives, teachers, parents, and adolescents (including the student and teacher ambassadors see below). To encourage participation, in eight countries, study participants were compensated with a voucher, personalised feedback, and a certificate confirming their engagement upon study completion. One country did not permit this kind of compensation. An average of one teacher and two students per school were recruited as school ambassadors, who collaborated with the researchers to design the study app in an appealing way and helped assuring the clarity and comprehensibility of study materials such as participant information sheets and consent and assent forms. Several school-based and app-based strategies were implemented to achieve the 60 % target retention rate. App-based measures included automatic push notifications with subsequent reminder notifications to alert participants about upcoming surveys, a three to four weeks retention period to provide sufficient time for completing the main surveys, and a gamification element for filling in surveys that was collaboratively developed with study ambassadors. School-based strategies included survey completion during class hours where feasible, interactive visits by researchers at schools to distribute flyers and remind study participants of upcoming surveys and the value of their contribution, and flyers and reminders from class teachers or school representatives.

2.3. Instruments and assessment strategy

The study variables of Cohort 1 were selectively chosen based on the logic model of PUI that was developed in the basis of current models on PUI [7,20] and convergent evidence on the development and maintenance of PUI [4]. Aligned with our logic model (see Fig. 1), we adopted a systematic longitudinal approach to studying PUI, aiming to elucidate how key multifactorial determinants influence its progression and to identify reliable predictors of risk factors as targets for tailored interventions.

2.3.1. Assessment via the BootstrApp

A digital assessment tool, the smartphone application '*BootstrApp*', was co-created to enable an economic and dynamic assessment tool for Cohort 1.

The development of the assessment tool *BootstrApp* for Cohort 1 started in July 2023 and followed a user-centred approach involving the target group of 12–16-year-old adolescents from schools in France, Germany, Hungary, Lithuania, Netherlands, Portugal, Spain, Switzerland, and United Kingdom in three major co-creation activities. These three activities included two focus group sessions with nine 12–15-year-old adolescents from Ulm, Germany as well as one Bootcamp together with 12–16-year-old student ambassadors and teacher ambassadors from all nine countries. The two 2.5 to 3-h long focus group sessions took place on December 16, 2023 and January 27, 2024 and were reimbursed with 25€ vouchers per session. The first focus group session focused on the conceptual background of the assessment tool including general user needs and demands for the *BootstrApp*, attitudes and framing of mobile sensing, as well as the motivation to use the *BootstrApp*. The second focus group session focused on the implementation of the *BootstrApp*, specifically the *BootstrApp* design, the *BoostrApp* workflow, and the motivation to use the *BootstrApp*. Based on the most feasible suggestions from both focus group sessions, the *BootstrApp* design and workflow was updated and a more elaborate reward system was developed, resulting in a first prototype of the *BootstrApp*. In the third co-creation activity, the Bootcamp, three different parts were included. First, an online validation of the first prototype of the *BootstrApp* was conducted from March 4–15, 2024 with 35 student ambassadors, 21 teacher ambassadors, 5 youth experts aged 18–25 (EXMH Bootcrew), and 16 researchers. Second, a face-to-face interdisciplinary validation workshop from March 14–16, 2024 was conducted to address the issues found in the online validation and brainstorm on solutions regarding the comprehensibility and the visuals of the *BootstrApp*, the integration of the BrainPAC games, the motivation to use the *BootstrApp*, and the storytelling for the *BootstrApp*. Third, an online fine-tuning exercise after the bootcamp involved three actions: 1) student and teacher ambassadors who did not attend the bootcamp voted on their preferred storyline for the app, 2) a survey was sent to student ambassadors and young experts to conduct a final vote on the preferred storyline, and 3) young experts, researchers and the app development team decided on useful FAQ's to be included in the *BootstrApp*.

The final *BootstrApp* assessment tool entails the 6-month assessment of Phase 1, including questionnaires, mobile sensing, and games (see Fig. 3). The games are integrated automatically in the *BootstrApp* workflow via a deep link to and from its sister app, the *'Dragon Game App'*. The final co-created story line of the *BootstrApp* involves an astronaut whose rocket crashes and who gets lost in space. In level 1 of the App, the study participants are helping the astronaut to fix his rocket and in level 2, the study participants are helping the astronaut to find his way back home to planet earth. In order to do so the participants earn space coins for each answered question and astronaut themed badges for each assessment block (nine level-1 badges: 1. oxygen, 2. jetpack, 3. manual, 4. fire, 5. rollercoaster, 6. welding helmet, 7. wrench, 8. rocket fixed, 9. fuelling up; seven level-2 badges: 10. telescope, 11. planet overview, 12. golden planet, 13. water planet, 14. purple planet, 15. moon, 16. earth). Two additional master badges could be earned: the 'Coin Master' badge and the 'Time Master' badge. The "Coin Master" badge was earned if the study participant answered more than 90 % of all questions. The "Time Master" badge was earned once the study participant completed the 6-month assessment. Moreover, if they answered more than 90 % of all questions, study participants received a certificate of completion within the *BootstrApp* as well as personal feedback on their screen time, internet use, internet activities, results of the BrainPAC games, proneness for misinformation, personality, and Fear of Missing Out (FoMO). In addition, they received a voucher outside of the *BootstrApp* if they answered more than 90 % of all questions.

The *BootstrApp* and its sister app the Dragon Game App are available for the two major smartphone operating systems, Android and iOS (65% and 34% market share among smartphones in Europe, respectively), making it accessible to nearly all smartphone users [54]. Given the continuous evolution of operating systems, including the addition and removal of functionalities, a minimum operating system version needed to be defined during development. For *BootstrApp*, this is Android version 10 or iOS version 15.6, primarily due to the use of mobile sensing functionalities (see section *Passive Digital Monitoring*). For the Dragon Game App, the Android version 6 or iOS version 16.1 are the minimum operating system versions. The available app languages are Dutch, English, French, German (CH-German and DE-German), Hungarian, Lithuanian, Portuguese, and Spanish. The *BootstrApp* and the Dragon Game App were provided to the study participants via the Google Play Store (for Android users) and the Apple App Store (for iOS users). Also, a direct download of the Android Package (.apk file) was provided to speed up the start of data collection. Direct downloads were an alternative way to install an app on Android smartphones without the approval of Google for the app.

2.3.2. *Instruments*

In the following, all measures and paradigms used in Cohort 1 are described, organised by category. For the assessment workflow, refer to Fig. 3. All measures were mandatory expect when outlined otherwise in the description.

2.3.2.1. Baseline (t0) and Baseline + 6 months (t2). **Demographic information (t0 only)** was collected on age, sex, gender, and year group at school. For sex and gender, a two-step approach was selected, as suggested by Magliozzi et al. [55]. This approach captured the assigned sex at birth (i.e., "Were you born as a boy or a girl? We mean here how your parents registered you with the municipality") and the current gender identity (i.e., "What do you feel you are? Your feelings may be different from how you were born"). For the latter, answer options ranged from "a boy", "a girl", "between a boy and a girl", "both a boy and a girl", neither a boy or a girl", to "not sure". For both sex and gender items, additional "prefer not to say" answer options allowed children to skip these questions. The year group at school needed to be typed into open text fields in the survey.

2.3.2.1.1. Generalised PUI. The **Compulsive Internet Use Scale** (CIUS; [56]) was used in its five-item short version (S-CIUS; [44]) to assess the severity of compulsive internet use. The items (e.g., "How often do you find it difficult to stop using the Internet when you are online?") were rated on a five-point Likert scale for the frequency of occurrence from 0 = never to 4 = very often. With only five items, the S-CIUS serves as an ecological measure of PUI in our survey. It was specifically added to our protocol to be assessed repeatedly, providing a frequent measure of PUI to inform our machine learning algorithm and is therefore the primary endpoint quantifying PUI. The S-CIUS shows good validity and reliability [44].

The **Problematic Internet Use Questionnaire** (PIUQ; [57]) was used in its 9-item short version (PIUQ-9; [42]). The PIUQ measures specific problems associated with the use of the internet that result in three themes, including obsession, neglect, and control disorder. Nine items (e.g., "How often do you spend time online when you'd rather sleep?") were answered on a five-point Likert scale from 1 = never to 5 = always. Higher sum scores of the PIUQ indicate that problems happen more frequently to individuals. The PIUQ-9 amplifies the measurement of adverse consequences associated with PUI and is therefore used as the second primary variable quantifying PUI. The PIUQ shows good reliability in different languages [42].

The **Internet Severity and Activities Addiction Questionnaire** (ISAAQ-10; [38]) is a two-part screening instrument that was used to assess the severity of PUI (Part A) and the time dedicated to non-work and non-study related internet activities (Part B). Part A consists of ten items on general PUI (e.g., "How often do you find yourself loosing track of time while engaging on an internet related activity?"). Part B consists of ten items listing specific online activities (e.g., online shopping, skill games & time wasters, streaming media). Items of both parts were answered on a six-point Likert Scale from 0 = not at all to 5 = all the time. The ISAAQ shows good psychometric properties across cultures [58]. Next to diagnostic criteria for addiction, the ISAAQ incorporates other relevant concepts known to be involved in PUI, including impulsivity and compulsivity. The cross-national applicability and the multi-conceptual measurement of PUI make the ISAAQ an important variable quantifying PUI.

To further specify unstructured, **general surfing activities**, an open text field asked for the most common activity done when using the web browser (i.e., "What do you usually do when you're on the internet using your browser?").

2.3.2.1.2. Specific forms of PUI. The **Assessment of Criteria for Specific Internet-use Disorders** (ACSID-11; [28]) was used in a 5-item short version. The ACSID-5 evaluates symptoms of five specific forms of PUI (i.e., problematic online gaming, online buying-shopping, pornography use, social networks use, and online gambling) according to ICD-11 criteria [9], with one item per criterion. These criteria include impaired control, increased priority, continuation and escalation, functional impairment, and marked distress. The five items of the ACSID-5 were rated on a two-fold response format assessing frequency (0 = never, 1 = rarely, 2 = sometimes, 3 = often) and the intensity of the symptom experience (0 = not at all intense, 1 = rather not intense, 2 = rather intense, 3 = intense) within the past 12 months. With the validation of the ACSID-5 still pending, its long form shows good psychometric properties [59]. Next to our variables measuring generalised PUI (i.e., S-CIUS, PIUQ-9, and ISAAQ-10), the ACSID-5 follows the most recent approach of the ICD-11 to quantify an addictive nature of specific forms of PUI.

The **Cyberchondria Severity Scale** (CSS; [60]) was used it its 12-item short version (CSS-12; [32]) to assess a form of anxiety where online health research causes distress to the searching individual. Items (e.g., "I read different web pages about the same perceived condition") represent symptoms of cyberchondria that were rated for the frequency of their occurrence on a five-point Likert scale from 1 = never to 5 = always. All items can be summed up for a total score with higher scores indicative of more frequent symptoms. The short CSS-12 shows good validity without sacrificing the solid psychometric properties of the original version and has already been used in young people in its long version [32].

2.3.2.1.3. Health related quality of life and wellbeing. The **EuroQol Five Dimensions for Youth** (EQ-5D-Y; [35]) was used as a child-friendly measure of general health status and as behavioural risk factor surveillance. Health in different domains (i.e., mobility, doing usual activities, having pain or discomfort, feeling worried, sad or unhappy) were rated with formulated response options (e.g., "I have no/some/a lot of problems doing my usual activities") which are evaluated in a descriptive system commonly used in health economic evaluations. In addition, a vertical, graduated Visual Analogue Scale (VAS) was displayed to rate the level of own health between 0 (the worst) and 100 (the best health state he/she can imagine).

The **Paediatric Quality of Life Enjoyment and Satisfaction Questionnaire** (PQ-LES-Q; [43]) was used as a measure for the clinical status of children and adolescents. Young people were tasked to consider each item and indicate their response to the question "Over the past week, how have things been with ... (e.g., your health, your mood or feelings)" using the response categories of 1 = very poor, 2 = poor, 3 = fair, 4 = good, 5 = very good. The first 14 items are summed to form a total score, which can be reported as either the raw score or as percentage maximum possible, with higher scores indicating greater enjoyment and satisfaction. In addition, there was a single item "Overall, how has your life been?", which allowed subjects to summarise their experience in a global rating. The PQ-LES-Q shows good reliability in young people [43].

2.3.2.1.4. Mental health. The short **Depression Anxiety Stress Scale** (DASS-21; [33]) was used to assess symptoms of depression, anxiety, and levels of stress. 21 items on three subscales (i.e., depression, anxiety, stress) with seven items each (e.g., "I found it difficult to relax") were answered on a four-point Likert Scale ranging from 0 = did not apply to me to 3 = applied to me very much or most of the time. Higher sum scores indicate higher expressions of anxiety, depression, and stress level. Validation studies show good reliability and validity among young people [61].

The **Short Obsessive Compulsive Disorder Screener** (SOCS; [46]) was used as self-report measure for obsessive compulsive disorder symptoms in young people. Seven items (e.g., "Are you particularly fussy about keeping your hands clean?") tasked subjects to rate how much they engaged in certain thoughts or behaviours on a three-point Likert scale with 0 = no, 1 = a bit, and 2 = a lot. Higher sum scores indicate greater obsessive compulsive disorder symptoms. The SOCS shows good reliability in children and adolescents [62].

The **Strengths and Difficulties Questionnaire** (SDQ; [45]) was used to assess emotional and behavioural difficulties. 25 items measured difficulties in four domains, namely emotional symptoms, conduct problems, hyperactivity/inattention, and peer relationship in addition to strengths in prosocial behaviour, with five items per domain. Each item (e.g., "I am restless, I cannot stay still for long") was answered on a three-point Likert scale with 0 = not true, 1 = somewhat true, and 2 = certainly true. The four difficulty-sub-scales can additionally be summed up to one sum score. Higher sum scores for each sub scale indicate greater difficulties, or prosocial strength, respectively. The SDQ shows good reliability in screening child psychiatric disorders in community samples [63] and has been used in more than 4000 research studies, so a wide range of comparable data is available (Youthinmind.com | Promoting the Well-Being of Youth Around the World). We use the SDQ not least because, in addition to any weaknesses, we want to explicitly assess the strengths and thus the resilience potential that the young people have.

2.3.2.1.5. Stigma. The **Paediatric Self-Stigmatization Scale** (PaedS; [41]) was used to measure self-stigma in children. The subscale "self-stigma" specifically refers to internalised shame regarding own feelings and emotions. It consists of five items (e.g., "How often do you feel people may not like you if they know you have difficult feelings or behaviour?") which were answered on a four-point Likert scale from 1 = very rarely to 4 = very often. The scale shows good psychometric properties [41].

2.3.2.1.6. Substance use. In line with the National Institute on Alcohol Abuse and Alcoholism [64], two items were used that can reliably detect **early risk in adolescents' alcohol consumption**. They vary slightly in their wording and their order according to middle and high school. One question asked for the friends' drinking behaviours (e.g., "Do you have any friends who drank beer, wine, or any drink containing alcohol in the past year?") and a second question asked for their own drinking behaviour (e.g., "How about you – in the past year, on how many days have you had more than a few sips of beer, wine, or any drink containing alcohol?" Details of risk assessment are explained in the associated YouthGuide [64].

2.3.2.1.7. Cognitive assessment. The **BrainPAC-enhanced value-modulated attentional capture** (VMAC; [30]) task was used to measure the tendency to develop reward-related attentional biases [65] which is a form of conditioned responding that reflects affect regulation capacity and a predisposition toward developing addictive behaviours [66]. In this task, participants search for a target stimulus (player on their team) among distractors (players on opposite team, one with brightly coloured hair) on each trial. The faster they find and respond to the target, the more points they earn. Critically, the colour of the player's hair can be one of two colours on any one trial, and the colour signals the size of the reward available on the current trial, such that one colour (the high-reward colour) signals that a large reward is available, and the other (low-reward) colour signals that a small reward is available. Notably, while the colour of the distractor signals reward magnitude, it is never the target that participants respond to in order to receive the reward. That is, the player with the coloured hair is never the player that participants must kick the ball to get the reward. Thus, distractors have a Pavlovian, but not instrumental, relation to reward. In 'sign-trackers', that is, those with reward-related attentional biases thought to be at risk of PUI [67], responses to the target are significantly slower for trials with a high-reward distractor compared to low-reward distractor (i.e., the VMAC effect, as indexed by the VMAC score). This suggests that the signal of high reward is more likely to capture participants' attention, slowing their response to the target – even though this enhanced capture is counterproductive. We extended the above VMAC task to include a reversal phase (referred to as the VMAC-reversal, or VMAC-R task), where the relation between distractor colour and reward in the training phase is reversed in the subsequent (reversal) phase. This extension is designed to gauge rigidity and persistence of reward-related attentional biases [67].

The **BrainPAC-enhanced Stop-Signal-Task** (SST; [30]) was used to measure response inhibition. We found response inhibition to be reliably affected compared to controls (effect size g = 0.42 (s.e. = 0.17–0.66)) in a meta-analysis of PUI studies, irrespective of the form of PUI [68]. Therefore, we expect SST performance to reflect generic PUI risk. In the BrainPAC-enhanced SST, players engage in a battlefield game to replenish arrow supplies of team-mates on the battlefield. Players press left or right to move the character up the grid to restock arrows as quickly as they can when signalled by one of two archers (i.e., the go signal). In a minority of trials (i.e., 30 %), the enemy dragon breathes fire on the battlefield (i.e., the stop signal), necessitating the player to withhold their response. We incorporated a reward system to incentivise faster go responses using a points system (and reduce the chance of players 'waiting' for the stop signal as a strategy) as previously recommended by consensus. A progress bar and sound effects were included to further enhance engagement. There were 10 practice trials and 150 test trials, with SSD starting at 200 ms and stair-cased by 50 ms. The key parameter (stop signal response time; SSRT) is calculated using integration methods [69].

2.3.2.2. Baseline + 3 months (t1)

2.3.2.2.1. Person's characteristics. The **10-item version of the Big-**

Five-Inventory (BFI-10; [29]) was used to assess the five personality dimensions openness, conscientiousness, extraversion, agreeableness, and neuroticism on five subscales with two items each. Each item (e.g., "I am comfortable, prone to laziness") was rated on a five-point Likert scale from 1 = does not apply at all to 5 = fully applies. Each dimension is assessed via one item with positive and one with negative polarity. After recoding respective items with negative polarity, mean scores are calculated for the five different dimensions where higher scores indicate a higher expression of the respective personality dimension. The structure of the BFI and its correlations with socio-psychological variables are age-invariant [70] and the BFI has already been used among adolescents [71]. Further, the BFI-10 shows reliable psychometric properties [72].

The **Urgency – Premeditation – Perseverance - Sensation Seeking - Positive Urgency** (UPPS-P; [73]) impulsive behaviour scale was used in its short 20-item version for children (UPPS-P-C; [47]) which uses simplified and age-appropriate language. It measures five facets of impulsivity on respective subscales, namely negative urgency, lack of premeditation, lack of perseverance, sensation seeking, and positive urgency. Each item (e.g., "I usually think carefully before doing anything") was rated on a four-point Likert scale from 1 = I agree strongly to 4 = I disagree strongly where sum scores are built for each subscale. The short UPPS-P shows good psychometric properties across cultures (e.g., [74]).

2.3.2.2.2. Behavioural adaptation. The **Cambridge–Chicago Compulsivity Trait Scale** (CHI-T; [31]) was used to assess aspects of compulsivity covering the need for completion or perfection, reward seeking, desire for high standards, and avoidance of situations that are hard to control. 15 items (e.g., feeling comfortable when things are done right) were rated on a four-point Likert scale from 0 = strongly disagree to 3 = strongly agree with higher sum scores indicating more compulsive tendencies. The scale has already been used in student samples [75] and shows good psychometric properties [31,76].

The **Internet Severity and Activities Addiction Questionnaire – Eating Disorders** (ISAAQ-ED; [39]) was used to capture internet activities that are related to eating disorders. It assesses the frequency of ten such activities (e.g., Pro-Eating Disorder websites or pro-Eating Disorder social media (includes spending time engaging with online content that promotes living with an eating disorder in a positive way; Calorie tracking (includes using a calorie tracking App or website)) on a six-point Likert Scale ranging from 0 = not at all to 5 = all the time. The ISAAQ-ED is not validated yet and considerations on a scale score are pending. It serves as an exploratory variable in our study protocol.

Vaccine hesitancy was assessed to take post-pandemic consequences into consideration. Vaccine hesitancy may be a manifest form of cognitive inflexibility, a factor rendering individuals vulnerable to developing addictive and compulsive disorders, including PUI. For the purposes of our study (e.g., general vaccine hesitancy instead of Covid-19-specific vaccine hesitancy, child-friendly items without considering "government programmes" or "pharmaceutical companies"), we integrated and modified items from three different scales, the Oxford Covid-19 Vaccine Hesitancy Scale (three items; [77]), the Vaccination Attitudes Examination (four items; [78]), and the Vaccine Hesitancy Scale (four items; [79]). 11 items were answered on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

2.3.2.2.3. Operant learning mechanisms. The **Experience of Gratification Scale and Experience of Compensation Scale** (EGS & ECS; [34]) was used to assess the experience that individuals have while using the internet. Six items for the gratifying experience (e.g., "While using the internet I feel powerful") and six items for the compensating experience (e.g., "While using the internet I feel less worried") were answered on a five-point Likert scale ranging from 0 = never to 4 = very often. The EGS subdivides into the factors experience of hedonism and gratification of needs whereas the ECS subdivides into two factors, compensation of stress and compensation of needs. For each factor, subscale, and for the whole scale, mean scores are calculated with higher values indicating greater reinforcement experiences. The EGS and ECS show good psychometric properties [34].

The **Internet Use Expectancies Scale** (IUES; [40]) was used to assess consequential expectancies of internet usage. The IUES divides into one subscale for gratifying (e.g., "I use the internet to experience pleasure") and compensating (e.g., "I use the internet to avoid loneliness") expectancies. Items were answered on a six-point Likert scale ranging from 1 = completely disagree to 6 = completely agree. A mean score can be calculated for the subscales and the whole scale where higher scores are indicative of more positive or avoidance reinforcement mechanisms regarding internet usage. The IUES shows good psychometric properties [40].

The **Fear of Missing Out Scale** (FoMO; [80]) was used in an adapted version [37] that can assess an online-specific FoMO with seven items (e.g., "I'm afraid of not being up to date on my social media") next to a general trait-like FoMO with five items (e.g., "I feel insecure when I do not know what my friends are up to"). The items were answered on a five-point Likert scale ranging from 1 = completely disagree to 5 = completely agree with higher mean scores indicating a higher expression of FoMO.

2.3.2.2.4. Academic performance. To assess **school performance**, children were asked to report their best and their worst school grade from the last school year. Further, their confidence in school subjects was assessed (i.e., "How confident do you feel about your ability in …"). Five subjects (i.e., "in maths", "in reading and [target language]", "in sciences (e.g., biology)", "in history and social sciences", and "in sports") were rated on a five-point Likert scale ranging from 1 = not confident at all to 5 = very confident).

2.3.2.2.5. Physical health. Children were asked to type their height and weight into open text fields to generate the **Body Mass Index** (BMI) of each participant. In acknowledgement that young people may be apprehensive to disclose details of their physical appearance, this question was not mandatory and involves an additional answer option "prefer not to say".

To assess how often children usually engage **physical activities**, they answered a single-item to rate the frequency of sportive or other engaging activities. The item "How often do you join sports or do activities that make you move and be active in your free time?" were rated on a five-point Likert scale from 1 = never to 5 = very often.

2.3.2.2.6. Internet literacy. **Proneness for misinformation** on the internet was assessed using a single-item (i.e., "What percentage of the information on the Internet do you think is true?") which was answered on a VAS ranging from 0 = I think nothing is true to 100 = I think everything is true.

To capture the extent to which an individual already tried to **limit their internet usage**, we asked three questions where the first one acted as a turnout question. Question one (i.e., "How hard have you tried to reduce your online activity in the last four weeks?") was answered on a four-point Likert scale from 0 = not hart at all to 3 = hard). If the answer was at least one, then the two sub-sequent questions unfolded. Question two asks for the reasons of restriction, giving a multiple-choice answer format to tick one or several reasons (e.g., "My parents thought I was online too much"). Question three asked for strategies to limit online activities with a multiple-choice answer format (e.g., "By a time limiter (e.g., on the smartphone)"). Variables are used exploratory in our study protocol.

2.3.2.2.7. Psychosocial factors. The subjective **family functioning** of children's families was assessed with two items focusing on relationships (i.e., "How do you rate the quality of relationships in your family?") and communication (i.e., "How do you rate the communication in your family?"). Both items were answered on five-point Likert scales ranging from 0 = poor to 4 = excellent. An additional answer option to skip this question was offered (i.e., prefer not to say).

The socioeconomic background of the children's families was assessed using items from the **Family Affluence Scale** (FAS; [36]). We decided on reducing the questionnaire to three items (i.e., "Does your family own a car, van, or truck?"; "How many bathrooms (room with a bath/shower or both) are in your home?"; "Does your family have a dishwasher at home?") to have children not reflecting too much about their own poverty (if this was the case). The bifactor analysis of Torsheim et al. [36] revealed that the selected three items represent the general factor best when averaging loadings for eight countries.

2.3.2.3. Ambulatory assessment (around t0 and around t2). An ambulatory assessment with structured diary questions (as used in [81]) captured different mental state domains relevant to self-management of internet use (i.e., cognition, affect, perception, behaviour) alongside 'real time' contextual information. Participants completed a 5-min end of day assessment over two seven-consecutive day periods (around t0 and t2). The first assessment started Mondays after the completion of t0 to ensure comparable starting points across assessments. The second assessment started seven to 13 days before the start of t2. This prevented an excessive burden with questionnaires and ensured that the Phase 1 assessment was finished after 190 days. The survey included questions about temptation (i.e., "How strong was the temptation to use … today?"), mood (i.e., "How was your mood today?"), and stress (i.e., "How stressed did you feel today?"). If participants indicated that they had used the internet today (1 = Yes, 0 = No), the experience of pleasure (i.e., "How strong was the experience of pleasure while using …?"), the experience of relief (i.e., "How strong was the experience of relief while using …?"), and interference with daily activities (i.e., "How strong did the use interfere with other things?") was assessed. All items were answered on ten-point Likert scales with anchors according to the measure of interest (i.e., intensity, quality etc.). If participants indicated that they did not use the internet today, they were tasked to answer the same questions for another activity that they did that day (typed into an open text field). This should prevent children from learning that they can quit the ambulatory assessment earlier by clicking "No".

2.3.2.4. State affect regulation and state inhibitory control (repeated every 8 days throughout study period). Two items were designed to capture fluctuations in the two key psychological constructs relevant to BootStRaP: affect regulation and inhibitory control. One item assessed emotional instability (i.e., "How has your mood changed the last few days?") as an indicator for affect regulation problems. It was answered on a ten-point Likert scale ranging from 1 = no change to 10 = like a yo-yo. A second item assessed impatience (i.e., "How impatient have you felt the last few days?"), a core aspect of inhibitory control, which reflects the participants' ability to delay gratification or manage impulses effectively. It was answered on a ten-point Likert scale ranging from 1 = not at all to 10 = very. By measuring these constructs every eight days, this protocol aims at identifying dynamic patterns in mood regulation and impulse control over time. The time interval was chosen to ensure that participants were asked on different weekdays every week.

2.3.2.5. Passive digital monitoring (continuously throughout study period). Digital phenotyping and mobile sensing [50] mines behavioural data (e.g., circadian rhythms, physical movement, internet usage) passively, without user involvement by sensor devices to overcome disjunctions between self-reports, informant reports and objective data and prevent experienced time distortions [82] due to the immersivity and platform design of many online platforms [83,84], which might be a critical indicator of PUI [85,86]. We therefore recorded digital footprints with the '*BootstrApp*' (see above) across the whole assessment period from t0-t2, providing insights into a myriad of variables linked to PUI. Both major smartphone platforms (Android and iOS) allow this kind of data collection for a wide range of variables, though their capabilities differ in certain aspects, particularly regarding data structure (Apple SensorKit, 2025; Android API, 2025). For the collection of certain variables, platform-specific permissions were also required (Apple Research and Care, 2025). Each data type category encompassed individual attributes. For example, the "Location" category included attributes such as latitude, longitude, altitude, speed, and timestamp. The BootstrApp collected mobile sensing data within these technical capabilities, but only to the extent necessary to address the specific research questions. Data were anonymised (for details see section 2.5 Data management and quality control), and the temporal granularity of the collected data was explicitly defined. For instance, GPS locations were collected only every 15 min, even though more frequent sampling would be technically feasible. This approach not only enhanced data protection but also conserved resources on participants' devices and within the server backends (e.g., battery life, storage, data transfer, and costs).

Beyond actual app usage and the already mentioned GPS locations, this methodology provides an overview of the overall digital behaviour of the user, for instance, overall screen time, log in frequency, duration of each smartphone session and so forth. See Table 1 for a list of the collected mobile sensing categories, differentiated by operating system (also see a related app describing possibilities in this area; [49]). Smartphone usage was time stamped and the time variables can be also exploited in the later conducted analysis, for instance via machine learning. From the recorded digital footprints not only insights into technology use can be ascertained, but also psychological states/traits can be "sensed" via the passive smartphone log data, as different forms of smartphone use are associated with many important psychological variables [51,85,87].

2.3.3. Translation protocol

All instruments used in the BootStRaP project were initially available (or created) in English. Instruments that needed translation into one or several of the remaining seven target languages (i.e., Dutch, French, German, Hungarian, Lithuanian, Portuguese, Spanish) were translated according to our translation procedure. This procedure followed a standardised four-step process to ensure linguistic and conceptual equivalence across target languages. First, each instrument, initially available in English, was independently translated into the target language (e.g., Spanish, German, Lithuanian) by two native speakers of the target language from the recruitment centres of WP1. Second, the two translators discussed to resolve discrepancies and determine translation challenges. Together, they produced a consensus version in the target language. If disagreements persisted, a third person mediated to finalise the consensus. Third, the consensus version was translated back into English by a fluent English speaker, proficient in both languages. Fourth, the back-translation was reviewed and approved by an expert panel led by Professor Naomi Fineberg (University of Hertfordshire, UK). Yet, this process does not guarantee identical psychometric validity across languages. Following data collection, we will examine measurement invariance across languages to assess whether the psychometric properties of the translated instruments are comparable.

Table 1
Mobile Sensing data categories and support by platforms (* supported but, at the time of writing this paper, not yet fully approved by Apple for BootstrApp.)

Data category	Android	iOS
Device sessions	Yes (event based)	Yes (daily aggregated)
Contact list	Yes	Yes
Calls	no permission for study apps	Yes (aggregated)
SMS	no permission for study apps	Yes (aggregated)
Installed apps	Yes	Partial*
App Sessions	Yes	No
App Statistics	Yes	Partial (aggregated)*
GPS / Locations	Yes	Yes
Accelerometer	Yes	Yes*
Rotation Rate	Yes	Yes*
Pedometer	No	Yes (daily aggregated)*
Visits	No	Yes (daily aggregated)*
Device Information	Yes	Yes

2.4. Procedures

In a first step in some of the countries governments or responsible school authorities supported the project to ensure the most representative set of schools in the respective regions. Initial contact with schools: The schools were recruited via phone calls, e-mails, letters or direct personal contact. During an initial meeting to discuss details of the project implementation at each school, it was clarified that the participating schools are partner schools, meaning they are expected to take part in the entire project if possible and are also intended to benefit from the scientific exchange both in the medium and long term. After initial contact, parent evenings and school and class visits were implemented to give information, answer questions and support starting the study.

In every school, at least one ambassador was elected among the teaching staff and one within the student body, if possible. These were designated the "bridge builders". They were intimately involved in the project even in the initial recruitment phase. Ambassadors worked to foster the relationships between the schools and the researchers from the recruitment centres. They were available to answer questions about the project and participate in the bootcamps (see description below). The ambassadors ensured that the perspective of the students and the schools were given special consideration.

Parents or guardians were asked to provide consent (on behalf of the child) followed by child assent to take part in the study. Parent or guardian consent was obtained in paper format with a wet signature or electronically via the school's preferred process. Child assent took place online directly in the BootstrApp or was collected on paper, depending on local requirements and recommendations of ethic committees (see section on Ethical considerations).

There were three codes provided to the study participants. First, an access code allowed participants to use the BootstApp, as it was openly accessible in the app and google store. Second, an individual parent code ensured that consent and assent could be linked to the study participant in a pseudo-anonymised way. Third, a start code was entered whereafter data collection in the BootstrApp started automatically.

2.5. Data management and quality control

The BootStRaP study is managed and overseen by the University of Hertfordshire who provide the Quality Management System ensuring the trial is managed to the highest standards. The BootStRaP project's data management plan was created by the ULM University and is supported by a Data Sharing Agreement with all joint data controllers as signatories with local Data Processing Impact Assessments as required. The agreements conform to the GDPR Regulations (EU) 2016/679. All the study data, where possible, will be made freely available in an anonymised form at the end of the study and once the main study outcomes have been published, along with a range of supporting documents, code, and training materials.

By design, the study processes and procedures have been developed to ensure that the identities of the study participants are protected as strongly as possible. In particular, there will be no direct link between the identities of the study participants and the main study database. Participant data collected within the BootstrApp and the Dragon Game App are transferred in an encrypted form and then stored on secure EU servers, and the data is pseudonymised using a random code.

To reduce the potential for reidentification, potentially identifying information in subgroups of participants will be redacted. In particular, information about individual gender will be removed where providing that information will identify an individual.

Data stored on the mobile devices of the study participants were protected by built-in sandboxing mechanisms, such that by design no other third-party apps can access data from the BootstrApp or the Dragon Game App. Various approaches were used to anonymise mobile sensor data. Phone numbers were encrypted with strong one-way encryption hash algorithms (such as SHA-2). Location information (GPS) was protected by an algorithm that uses projection to anonymise locations, specifically the longitude. That is, before storage of GPS locations, a projection algorithm was applied to randomly offset each location point. This method preserved the relative distances and movement patterns between points while ensuring that the original geographic coordinates cannot be reconstructed, thereby protecting user privacy. The transformed data retains realistic spatial relationships, enabling analysis of mobility patterns and identification of location clusters without exposing actual locations. As a result, while the data behaves like true geolocation data in terms of distance and movement analysis, any attempt to map the coordinates would place them in arbitrary, non-identifiable areas, such as uninhabited regions or bodies of water.

Ethically, a pathway to identifying a study participant must be provided in exceptional circumstances, for example where there is a significant risk of harm to the participant or other people. The parental consent code will be linked to the participant's name, allowing the participant to be identified where necessary. The document providing the link is stored on location (either at the School or held by the country organiser), and separately from the main study database.

In case participants withdrew their consent to be part of the study, no new data was collected. Any identifying data that was collected by the BootstrApp and the Dragon Game App was removed from the smartphone of the study participants after deleting these Apps. Data that had already been collected cannot be deleted as processing the data requires anonymization, and ongoing data analysis already incorporated the collected data.

After completion of the trial and reporting of results, the anonymised data will be retained for at least 10 years for regulatory inspection. Data uploaded to repositories will be fully anonymised, and redacted where necessary.

2.6. Statistical analysis plan for Cohort 1

2.6.1. Machine learning

We apply classical machine learning (ML) and deep learning (DL) methods [50] to Cohort 1 to develop algorithms for predicting individuals at risk for PUI and identify actionable variables for application to subjects as intervention. We employ a novel pipeline [51,87] which integrates multivariate predictive models encompassing both classical (e.g., logistic regression, random forest) and modern methods such as deep neural networks. This pipeline is specifically designed to link individual-level assessments with outcome measures. It operates through a two-step process that leverages vast amounts of unlabelled mobile sensing data to generate enriched representations, thereby amplifying the underlying signal quality and enhancing predictive accuracy. In the first step, we transform raw mobile phone usage data into a structured representation using a combination of classical and deep unsupervised learning techniques. This involves i) clustering and manifold learning (e.g., UMAP) to identify natural groupings and underlying structures in the data, and ii) latent space embedding via autoencoders and self-supervised learning to extract compact, high-quality features. This enriched representation is designed to capture normative behavioural patterns as reflected in mobile usage and to identify deviations from these patterns on a weekly basis. In the second step, we apply supervised classification algorithms to estimate individual's risk for PUI, as indicated by their responses to the S-CIUS questionnaire (see section 2.3.2. Instruments). The core of this prediction relies on quantifying the degree of similarity between a subject's current mobile usage patterns and the established normative behavioural profiles derived in the first step. This two-step process leads to a more robust and improved risk estimation. Generalization and validation will be assessed using test (held-out) data and common cross-validation methods at the individual level. The contribution of single variables to the overall prediction is analysed using SHAP (SHapley Additive exPlanations) [88] which is expected to reveal actionable variables for the interventions (tested in Cohort 2 and 3). This approach has been validated previously and has guided the development of eHealth applications. The employment of ML and DL methods enables a massive data analysis, integrating both digital and clinical measurements to deliver algorithms that could (1) identify the at-risk and not at-risk population to develop PUI and (2) identify patterns predicting the utility of interventions. While forecasting complex psychological phenomena such as PUI may be an area of development across disciplines, recent work demonstrates that machine learning approaches can yield meaningful predictive accuracy in this domain (e.g., [89,90]). Building on this foundation, our models are designed to achieve robust individual-level risk estimation. BootStRaP will therefore make a substantial contribution by evaluating and strengthening empirical precision of algorithmic prediction in this field.

2.6.2. Psychological mechanisms proposed in the logic model of PUI

Using data from Cohort 1, we aim to validate (pathway-) hypotheses stated in the logic model of PUI (see Fig. 1). These analyses will employ Structural Equation Modelling (SEM) to examine the interplay between predisposing risk factors (e.g., impulsivity, compulsivity), affective and cognitive processes (e.g., reward-related attentional biases), and executive functions (e.g., inhibitory control) in explaining PUI. Measurement invariance across countries, languages, and genders will be tested to ensure comparability of constructs. Additionally, missing data will be handled using techniques such as multiple imputation or full information maximum likelihood (FIML), to prevent bias in parameter estimates. The model fit will be assessed using standard indices (e.g., Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI)) to ensure the validity of the hypothesised relationships. Finally, potential multicollinearity among predictors and indirect effects through mediators will be explored to test hypotheses of causal pathways within the logic model framework (see Fig. 1).

2.6.3. Health economic modelling

The health economics model employed in the BootStRaP project is designed to assess the cost-effectiveness of interventions targeting the prevention and management of PUI. This model integrates algorithm-based predictions and intervention testing, creating a robust framework for optimizing health outcomes while maintaining economic efficiency. The BootStRaP project's health economics framework centres around a cost-effectiveness analysis (CEA) to evaluate the benefits of interventions relative to their costs. The model integrates multiple dimensions, including psychological, social, and health outcomes, to determine the most efficient allocation of resources. These include direct costs (e.g., personnel, software development, and testing), indirect costs (e.g., administrative overhead, training, opportunity costs), and intervention-specific costs such as materials and logistics. Outcome metrics are based on improvements in self-management of internet use, reductions in PUI prevalence, and enhancements in mental health outcomes. Adolescents identified as at-risk for PUI, a group particularly vulnerable post-pandemic, are the primary focus. The inclusion criteria and participant selection ensure the generalizability of the model outcomes. The project uses advanced machine learning models to predict the likelihood of individuals benefiting from specific interventions. These predictions are factored into the economic model to ensure targeted and personalised delivery of interventions. Costs are calculated using actual expenditure data, aligned with the project's budget categories such as personnel costs which will be derived from time allocation and daily rates based on standard accounting practices. We will also use equipment costs reported as depreciated values over the intervention period. Subcontracting and procurement will include third-party costs for specific technical tasks or resource acquisition. Indirect costs are accounted for using a flat rate of 25 % of eligible direct costs, excluding subcontracting and other non-eligible categories. Performance indicators include changes in mental health scores, reduction in PUI behaviour, and societal outcomes like reduced healthcare utilization. Benefits are quantified in terms of quality-adjusted life years (QALYs) gained, a standard metric for health economics evaluations.

The project employs a stepwise approach for conducting CEA, ensuring methodological rigor and alignment with health economics standards. Cost data are gathered from all consortium partners and project beneficiaries, covering personnel, equipment, and intervention delivery. Effectiveness data are obtained from the digital screening and intervention platforms, measuring behavioural changes and mental health outcomes. Incremental cost-effectiveness ratios (ICER) compare the additional cost of the intervention to the additional benefits achieved. Results are benchmarked against willingness-to-pay thresholds to determine cost-effectiveness. Uncertainty in cost and outcome data is addressed through probabilistic sensitivity analysis (PSA). PSA involves running simulations with variations in input parameters to assess robustness. The budget impact analysis (BIA) estimates the financial implications of scaling up interventions across Europe. This complements the CEA by demonstrating affordability from a policy perspective. Different intervention types (e.g., digital vs. traditional methods) are compared to identify the most effective and economically viable approaches.

Cost-effectiveness results are stratified by demographic and geographic factors to inform tailored policy recommendations. Findings are synthesised into a policy toolkit. This includes actionable insights for policymakers and private entities, encouraging the adoption of interventions aligned with digital human rights and adolescent mental health protection. In the BootStRaP project, the EQ-5D and utility scales will be employed to measure health-related quality of life (HRQoL) in adolescents participating in interventions aimed at reducing PUI. The EQ-5D, particularly the EQ-5D-Y version tailored for younger populations, will capture key dimensions of wellbeing, including anxiety and depression, which are central to the project's focus on mental health. Utility values derived from EQ-5D responses will be used to calculate QALYs, a standard metric in cost-utility analysis, enabling the project to assess the cost-effectiveness of digital interventions compared to traditional approaches. These utility values, combined with cost data, will inform ICERs, guiding policy recommendations and resource allocation to optimise adolescent mental health outcomes across Europe and beyond. We will also use the Paediatric Quality of Life Enjoyment and Satisfaction Questionnaire (PQ-LES-Q), which measures quality of life based on the previous week's experiences. Data will be collected at baseline (t1) and after six months (t2), providing valuable insights into changes in HRQoL and the effectiveness of the intervention.

In the BootStRaP project, we propose the use of Discrete Event Simulation (DES) as a key methodological approach to model and evaluate the health and economic impacts of our intervention for PUI. DES is a flexible and dynamic simulation technique that models individual pathways and interactions over time, enabling the representation of real-world complexity in health systems and behavioural interventions.

The DES model will simulate the progression of individuals with PUI through various health states, reflecting the natural history of the condition and the potential effects of the intervention. Each participant will be treated as an individual "entity," with characteristics such as baseline health status, HRQoL, and socio-demographic factors. Events, such as the initiation of the intervention, changes in HRQoL scores, or the occurrence of adverse mental health outcomes, will be modelled to occur at specific time points, driven by probabilities derived from evidence-based inputs. The simulation will integrate data collected at baseline (t1) and six months (t2) from validated instruments like the EQ-5D-Y and the PQ-LES-Q. These data will inform the transitions between health states and the overall impact of the intervention.

The DES framework will allow us to account for variability and heterogeneity in participant responses, providing a nuanced understanding of both individual-level and population-level outcomes. Through the DES model, we will estimate the potential long-term health and economic outcomes of our intervention, including QALYs gained, healthcare resource use, and costs avoided. This approach will also enable us to test different intervention scenarios, optimizing delivery and identifying the most cost-effective strategies to reduce the health burden of PUI. By capturing the complexity of individual and system-level interactions, DES provides the foundation for evaluating the real-world feasibility and scalability of the proposed intervention.

3. Ethical considerations

The study is undertaken according to the principles of the International Council for Harmonisation of Technical Requirements for Pharmaceuticals for Human Use (ICH) Good Clinical Practice (GCP) guidelines and the relevant ethics and governance processes. Ethics approval had been sought by each site's local University Research Ethics Committee (REC) or other competent ethics committee for research with humans to allow for site specific ethics and governance procedures which may differ across the consortium (UK – University of Hertfordshire Health, Science, Engineering and Technology ECDA – LMS/SFUH/05626; Switzerland – Kantonale Ethikkommission Zürich - 2024-00896; Netherlands – The Scientific and Ethical Review Board (VCWE) of the Faculty of Behaviour & Movement Sciences, VU University Amsterdam – VCWE-2024-089; Germany – Universität Heidelberg, Ethikkommission der Fakultät für Verhaltens- und Empirische Kulturwissenschaften – AZ Bra 2024 1/1; Spain – Comité de Ética de la Investigación con Medicamentos Hospital General Universitario Gregorio Marañón; Hungary – Eötvös Loránd University, ELTE Eötvös Loránd University Faculty of Education and Psychology Research Ethics Committee – 2024/267; Portugal – Comissão de Ética (CdE) da Faculdade de Psicologia e de Ciências da Educação da Universidade do Porto – 2024-06-02b; France – Comité de protection des personnes Sud-Méditerranée – 2024-A01006–41; Lithuania – Lietuvos Sveikatos Mokslų Universitetas, Bioetikos Centras – 2024-BEC3-T-015).

Although in several countries some of the young people were old enough to provide informed consent for themselves, as all children were recruited through schools, we kept the process the same for all. Parents or guardians were asked to provide consent (on behalf of the child) followed by child assent to take part in the study (see section on Procedures).

Study participants are a school sample and therefore generally healthy young people, not patients. The study is observational by nature and does not include a treatment intervention. The study assessments are survey based, not expected to cause distress and mostly take the form of validated questionnaires. The study participants were informed that they could withdraw at any time without giving a reason. If participants experienced emotional distress, the study app included a dedicated submenu that signposted young people who require assistance on where to seek help via school based, local or national mental health support services.

In the realm of ethical considerations, it is also of relevance to highlight the importance of privacy of study participants [91]. Despite the study of sensitive data such as digital footprints from the smartphone plus survey data the privacy of study participants was protected by following a privacy by design strategy. Here, the smartphone itself was used as a computing machine running stats on phone use. The results of these analyses were then transferred to the study server. What was not transferred is what was exactly happening on the social media accounts (the sandboxing principle also hinders this), or where people were surfing to. Also, sensitive information (e.g., contacts details or exact locations) was anonymised first by one-way encryption algorithms or projection before they were sent to the server. All data transactions from the app to the server backend or vice versa were completely secured by modern encryption methods. As a result: by looking at the data of the study participants from the server, people cannot be re-identified.

4. Expected outcomes

Our findings with Cohort 1 will contribute toward A) developing advanced predictive algorithms that identify individuals at heightened risk for PUI by integrating behavioural, cognitive, and neurobiological markers, B) pinpointing actionable variables that can be leveraged for targeted preventative interventions, ensuring that selected strategies are personalised and adaptable for testing in the second phase of the project, C) refining and validating risk hypotheses outlined in the logic model of PUI, focusing on the complex interplay between predisposing risk factors (e.g., impulsivity, compulsivity), affective and cognitive processes (e.g., reward-related attentional biases), and executive functions (e.g., inhibitory control), D) conducting a comprehensive assessment of the health economic costs and societal impact of PUI in young people across Europe, quantifying both direct (e.g., healthcare utilization) and indirect (e.g., educational and occupational impairment) consequences.

In later phases, these insights will pave the way for the creation of scalable prevention strategies that can be implemented in educational, clinical, and digital settings. By integrating predictive algorithms with tailored preventative intervention strategies, the project will contribute to the development of a digital tool capable of real-time risk assessment and personalised feedback for young people and their families. The validated risk hypotheses will serve as a foundation for refining diagnostic criteria and improving early identification of at-risk individuals. Additionally, understanding the economic burden of PUI will provide policymakers with essential data for allocating resources efficiently, fostering the development of public health initiatives, and informing regulatory frameworks. These outcomes collectively support a holistic, evidence-based approach to mitigating PUI's mental health impact.

CRediT authorship contribution statement

Naomi A. Fineberg: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Conceptualization. **Annika Brandtner:** Writing – review & editing, Writing – original draft, Resources. **Nana Löchner:** Writing – review & editing, Software, Resources. **Christopher Kannen:** Writing – review & editing, Software, Resources. **Megan Smith:** Writing – review & editing, Conceptualization. **Simon Foster:** Writing – review & editing, Project administration. **Anita Meinke:** Writing – review & editing, Project administration. **Kristin Mosler:** Writing – review & editing, Project administration. **Shai Fine:** Writing – review & editing, Resources, Data curation. **Lior Carmi:** Writing – review & editing, Resources, Data curation. **Talia Friedman:** Writing – review & editing, Resources, Data curation. **Zsolt Demetrovics:** Writing – review & editing, Conceptualization. **Célia Sales:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Julia Jones:** Writing – review & editing, Conceptualization. **Hernâni Oliveira:** Writing – review & editing, Conceptualization. **Samuel R. Chamberlain:** Writing – review & editing, Conceptualization. **Konstantinos Ioannidis:** Writing – review & editing, Conceptualization. **Katalin Felvinczi:** Writing – review & editing. **Joseph Zohar:** Writing – review & editing. **Andres Roman-Urrestarazu:** Writing – review & editing, Methodology, Conceptualization. **Mart Susi:** Writing – review & editing, Conceptualization. **Julius Burkauskas:** Writing – review & editing, Visualization, Resources, Methodology, Conceptualization. **Katajun Lindenberg:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Ina Neumann:** Writing – review & editing, Investigation, Conceptualization. **Anja Huizink:** Writing – review & editing, Methodology, Conceptualization. **Carmen Moreno:** Writing – review & editing, Conceptualization. **Ornella Corazza:** Writing – review & editing, Conceptualization. **Teresa Silva Dias:** Writing – review & editing, Methodology, Conceptualization. **Meichun Mohler-Kuo:** Writing – review & editing, Methodology, Conceptualization. **Diane Purper-Ouakil:** Writing – review & editing, Conceptualization. **Erica Fongaro:** Writing – review & editing, Conceptualization. **Sara Fally:** Writing –

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Ethics approval and consent to participate

Ethics approval has been sought by each site's local University Research Ethics Committee (REC) or other competent ethics committee for research with humans to allow for site specific ethics and governance procedures which may differ across the consortium (UK – University of Hertfordshire Health, Science, Engineering and Technology ECDA – LMS/SFUH/05626; Switzerland – Kantonale Ethikkommission Zürich - 2024-00896; Netherlands – The Scientific and Ethical Review Board (VCWE) of the Faculty of Behaviour & Movement Sciences, VU University Amsterdam – VCWE-2024-089; Germany – Universität Heidelberg, Ethikkommission der Fakultät für Verhaltens- und Empirische Kulturwissenschaften – AZ Bra 2024 1/1; Spain – Comité de Ética de la Investigación con Medicamentos Hospital General Universitario Gregorio Marañón; Hungary – Eötvös Loránd University, ELTE Eötvös Loránd University Faculty of Education and Psychology Research Ethics Committee – 2024/267; Portugal – Comissão de Ética (CdE) da Faculdade de Psicologia e de Ciências da Educação da Universidade do Porto – 2024-06-02b; France – Comité de protection des personnes Sud-Méditerranée – 2024-A01006–41; Lithuania – Lietuvos Sveikatos Mokslų Universitetas, Bioetikos Centras – 2024-BEC3-T-015).

Author agreement

All authors have seen and approved the final version of the manuscript being submitted.

Submission declaration

This article is the authors' original work, has not received prior publication, is not under consideration for publication elsewhere, and if accepted, will not be published elsewhere in the same form, in English or in any other language, including electronically without the written consent of the copyright-holder.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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