Forensic Psychiatry and Big Data: Towards a Cyberphysical System in Service of Clinic, Research and Cybersecurity

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Abstract: The advent of big data and artificial intelligence has led to the elaboration of computational psychiatry. In parallel, great progress has been made with extended reality (XR) technologies. In this article, we propose to build a forensic cyberphysical system (CPS) that, with a data lake as its computational and data repository core, will support clinical and research efforts in forensic psychiatry, this in both intramural and extramural settings. The proposed CPS requires offender's data (notably clinical, behavioural and physiological), but also emphasises the collection of such data in various XR contexts. The same data would be used to train machine and deep learning, artificial intelligence, algorithms. Beyond the direct feedback these algorithms could give to forensic specialists, they could help build forensic digital twins. They could also serve in the fine tuning of XR usage with offenders. This paper concludes with human-centered cybersecurity concerns and opportunities the same CPS would imply. The proximity between a forensic and XR-supported CPS and social engineering will be addressed, and special consideration will be given to the opportunity for situational awareness training with offenders. We conclude by sketching ethical and implementation challenges that would require future inquiring.

1 INTRODUCTION

The recent context, the one motivating the present set of proposals, is fuelled by four related (or so we would contend) states of affair: the call for computational psychiatry (CPsy), the era of big data, the surge in artificial intelligence (AI) applications, and the ease of access to rapidly improving extended reality (XR) technology. Following the brief introduction of these four developments in the present section, the next two sections will delve in the crux of our proposals: a cyberphysical interface for clinical and research purposes, and its relationship with human-centred cybersecurity concerns.

The last decade has seen burgeoning discussions about CPsy. Itself inspired by computational neuroscience, it characterizes attempts to model mental illness biologically through multiscale levels (e.g., genetic, synaptic, neural circuit, social environment), all while assuming neuronal computations are at the core of both healthy and unhealthy psychology (Huys et al., 2016; Montague et al., 2012; Wang & Krystal, 2014). It is assumed that CPsy is to play a part in improving aetiological understanding and nosology of mental disorders, notably by liberating psychiatry from (too) stringent diagnoses, favouring instead data-driven approach which might help quantify symptoms dimensionally (Huys et al., 2016); in turn, improvements in therapeutics would be afforded, and to an extent, better personalized.

Directly related to both computational neuroscience and CPsy is the exponentially accumulating and numerous (big) data. This accumulation of data in various fields, notably the health industry (Chen et al., 2022a), is seen by many as a gold mine, empirical fuel to build better models, and in turn theories, about mental disorders and

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symptomatology. Data mining, the process of extracting useful information out of larger data sets, can be considered a component of CPsy (Montague et al., 2012).

The surge of big data and data mining in the sciences has led to the proposal of a new science that transcends standard statistics, "data science" (Dhar, 2012). The intensive need to process enormous amounts of data quickly and efficiently, algorithms under the umbrella term of "AI" are now developed and deployed to tackle this task. A prime example would be that of machine learning (ML) and deep learning (DL), and their multiple approaches (see Jordan & Mitchell, 2015; Mahesh, 2018; Ray, 2019; Shrestha & Mahmood, 2019). A common denominator of these approaches is better decision making, this, either by a human being, or another algorithm down the line. In the burning actuality, the public at large but perhaps academia more stingingly has been stormed by the release of efficient large language models (LLMs; see Naveed et al., 2024, notably their figured timeline).

Concluding the exposed context, the 1990' and early 2000' was the period where a first surge of research involving XR technologies hyped (virtual reality, then augmented reality, then mixed reality). However, it is only recently that such technologies have become, relatively: cheaper, more logistically versatile (e.g., size and weight of equipment, less cabling) and more immersive (e.g., better visual displays). A branch of cyberpsychology is versed into integrating XR technologies into psychotherapeutic protocols (e.g., Emmelkamp & Meyerbröker, 2021; Park et al., 2019; Wiederhold & Bouchard, 2014). Now, what can this broad context hold for forensic settings?

2 A FORENSIC MENTAL HEALTH' CYBERPHYSICAL SYSTEM

Forensics is understood here as any technical expertise or approach that relates to describing or understanding crime. Conversely, forensic psychiatry/psychology (FPsy) pertains to psychological factors (perhaps influenced by biology or social factors themselves; Barnes et al., 2022) that constitute risk factors of (re)offending. It is often assumed that crime is somewhat related to mental illness and psychopathology (Arboleda-Flórez, 2006).

Given the described context, a promising avenue for the merger of CPsy and FPsy is through a cyberphysical system (CPS), which would also be a mental health-oriented, medical, CPS (Chen et al., 2022a). Cyberphysics involves the merging of computational capabilities with physical processes (Lee, 2006). Jiang and colleagues (2020) position CPS as different from the Internet of Things (Atzori et al., 2010), the former having larger computational capacity, which in turn gives these computations control over the system (see also Chen et al., 2022a). As the same authors and others (Alam & El Saddik, 2017) note, data from physical sensors can be sent to a server, be computed upon, and in turn, give directives for sensor configurational change, forming a feedback loop. Such a loop makes CPS useful for human-machine interaction (HMI; Jiang et al., 2020), and of special relevance for FPsy, brain-computer interaction (BCI). Importantly, XR technologies can be implemented with/be part of HMI or BCI, implying part of the feedback would include XR content. So, what is advocated for, in an acronym-intensive nutshell: FPsy, following the insights of CPsy, should work within the confines of a CPS, as the latter leads to a more optimal HMI/BCI. Central to this are data storage and computational power, the subject of the next subsection. Figure 1 better situates the elements to be presented within the forensic-medical CPS framework proposed here.

2.1 Data Lake, Its Basic Structure and Content

The presented blueprint of data architecture management heavily relies on establishing a data lake, a multi-format big data (and any accompanying metadata) holder and modifier (Nargesian et al., 2019). A data lake implies a server with high-capacity storage. Costs for such infrastructure would vary according to the scope of the implemented CPS. Still, it is worth noting that forensic and medical (including psychiatric) institutions already have secured servers to support day-to-day operations. As such, adding the proposed data lake-supported CPS should not imply radical novelty to the existing computer infrastructure, and punctual adaptation for involved information technology services. For FPsy purposes, a list of non-exhaustive examples of retained data for any given offender would include criminal offense(s), psychiatric diagnoses and clinical notes, questionnaire and actuarial results, past and present physical conditions and diagnoses, medication schedule and posology, as well as behavioural and physiological indices. Such clinical information is

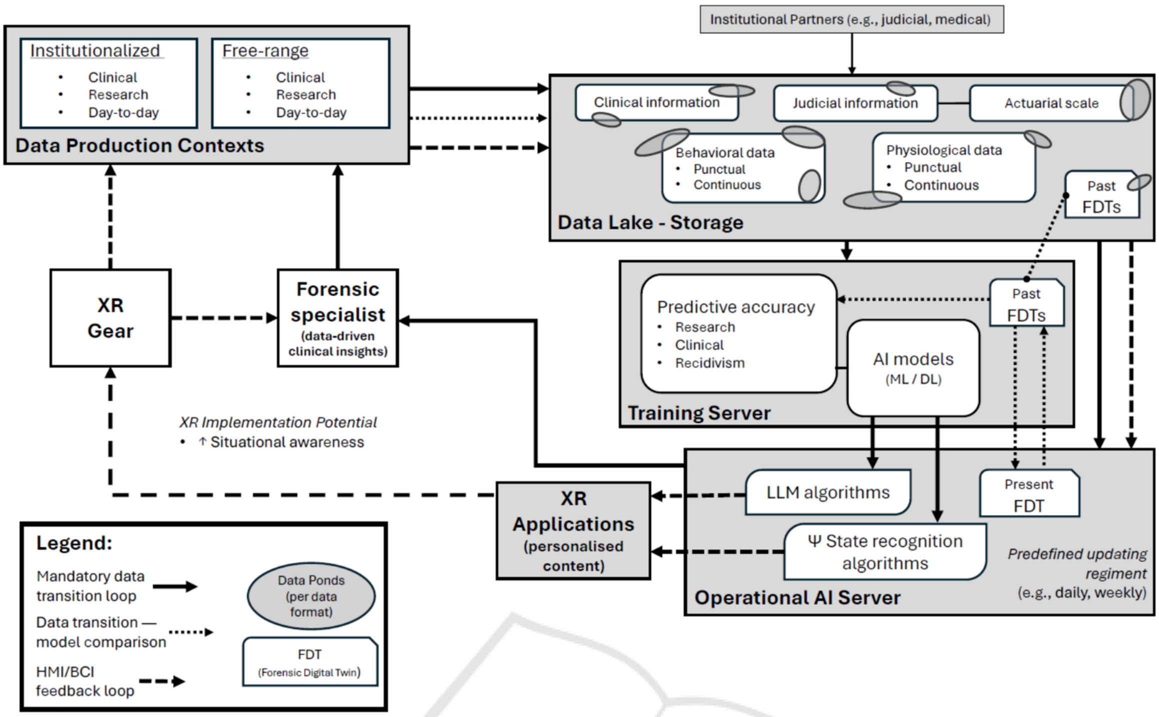

Figure 1: Data flows of the proposed forensic-medical cyberphysical system.

commonly centralised in medical settings, using features like the Open Architecture Clinical Information System (OACIS, Telus Health). More broadly, detailed considerations for a forensic CPS would likely benefit from considering medical CPS (see Chen et al., 2022a). Data-collection-wise, worth noting are LLM-powered applications that assist medical professionals when interviewing patients, for instance, by automatically taking notes. As these applications already see deployment in the anonymity bound healthcare service complex (e.g., CoeurWay), there implementing in forensic settings is arguably just as realistic.

Focusing on behavioural and physiological data, non-exhaustive examples: speech prosody and semantic content, heartrate, electroencephalography (EEG), electrodermal activity, eye-tracking, blinking, pupil dilation, brain structural scans and hemodynamic responses and salivary or blood hormonal levels. While some measurements can only be punctual snapshots in time (e.g., salivary cortisol) or inserted in research protocol efforts or be part of routine checkups, others can be continuous, perhaps 24/7 measurements (e.g., watch-monitored heartrate). At first glance, some of these measurements would appear to require intensive management efforts, such as laboratory analyses, followed by manual indexing of results. One should note however the rapid advancements in quick, app-monitoring-supported testing (e.g., salivary cortisol level; Eli Health).

To be maximally interpretable or useful, continuous physiological measurements likely require some data cleaning. A notorious example would be EEG, which beyond filtering choices, is also blighted by eye and other movement artifacts (Urigüen & Garcia-Zapirain, 2015). While there is no definitive nor consensual, solution to this challenge, automatic artifact removal readily exists (e.g., Goh et al., 2017; Pedroni et al., 2019), and their betterment is ongoing. The main point here is that for the data lake to serve in producing quality data autonomously and quickly (especially considering BCI), such automatic cleaning is warranted. In any case, the multiple types of data, and associated varying format and frequency of acquisition, all suggest highly individualized pre-processing pipelines and algorithms, in accordance with the notion of “data ponds”, a subdividing of processing architecture differing across data types (Inmon, 2016; Sawadogo & Darmont, 2021).

2.2 Behavioral and Physiological Monitoring with XR

The use of XR technologies within forensic settings offers a unique opportunity to probe the offender's psyche and behavioural patterns. We identify and focus on two main living settings: institutionalized and free-range. In turn, both could serve model building at both group (e.g., diagnosis) and individual levels.

2.2.1 Monitoring: Institutionalized or Free-Range

Institutionalization of forensic populations can be done in various settings (e.g., prison, secured psychiatric institutions, transition housing), all of which having in common a relatively high routine component (e.g., hours of getting up and curfew, eating hours, scheduled free-time and activity periods, etc.). In these controlled settings, it is relatively easy to integrate physiological measurements as those described above, again, them being either continuous or scheduled. It is further possible, especially in the latter case, to register subjective self-reports as well as clinical impressions or observations from caregivers and personnel. As for the former case, continuous measurements, they can be extensively investigated via research protocols incorporating XR technologies (Torous et al., 2021), said protocols implying stricter experiment control.

Such protocols would have to be designed and implemented with the specific institutionalisation settings in mind. The use of XR is already done in forensic settings (e.g., Boukhalfi et al., 2015; Renaud et al., 2014), but generally within a strict protocol of stimulus exposure. Even if more ecologically valid then, say, desktop tasks (Loomis et al., 1999), especially if LLMs were to be incorporated, one caveat of such protocols is that they may nonetheless influence or predispose offenders to a specific mindset or narrowed response options. In other words, offenders are still in a “task” setting, which is implicitly cognitively constraining. This further emphasises the relevance of spontaneous context exposure, as anticipation (conscious or not) on the offender's part is either absent or as in everyday living. XR-wise, it is tentatively hypothesized that AR would perform better than VR here, since the former keeps the individual more rooted in the real world. In other words, AR is more easily integrated as a new way of living then VR, a notion important to consider in the context of free-range monitoring. In the same vein, prolonged AR, coupled with speech recording, affords speech analysis (Corcoran & Cecchi, 2020) to be integrated within a CPS.

Free-range monitoring has the benefits of everyday living with little to no alterations. Its use with psychiatric populations to gain psychopathological insight has been advocated for, by using, for instance, social media and smartphone data (Gillan & Rutledge, 2021; Torous et al., 2021). In the continuous monitoring of offenders, it can be of interest to use AR, for three main reasons, its relatively: aforementioned less impactful disturbing of natural behaviour and inclinations, lesser development costs (Baus & Bouchard, 2014), lessened computational requirements (next subsection), and it favouring adaptational strategies (next section). While prone to its own challenges, free-range (cf, open world) ML might be a necessity for model quality (Zhu et al., 2024), and in turn, for any HMI/BCI success. More broadly for ML- and DL-based models, testing the predictive efficacy, or the lack-thereof (pushing the investigation towards the efficacy of each variable or configurations of), of institutional-data-built models for free-range situations is most relevant.

2.2.2 Nomothetic and Idiographic Prediction

A recurrent critique of conventional psychiatry is its generalizing tendency of both aetiology and treatment, perhaps routed in essentialisation (Brick et al., 2021; Hitchcock et al., 2022), at the expense of a more accurate and (perhaps necessary) personalized approach. Remembering the commitment of CPsy to overcome this pending issue, having data from monitoring a same individual at varying constraint levels (i.e., institutionalized contra free-range) might give key insights to co-enhance prediction in all settings (Gillan & Rutledge, 2021). More broadly, it has been noted that CPsy has had limited success in part due to an overcommitment to preexisting category fixations (e.g., as opposed to data-driven approaches; Rutledge et al., 2019), as well as insufficient flexibility in modelling approaches (Hitchcock et al., 2022). Central to the latter point would be lack of time and contextual consideration, or as the merger of the two would suggest, the need for a dynamical understanding of psychopathology (Hitchcock et al., 2022); the same could be said for our understanding of offending and any underlying role of psychopathology. The long-term, so longitudinal, monitoring advocated for could thus play a part in ending the gridlock of CPsy.

2.3 Towards Adjustment-Free HMI/BCI, Digital Twins, and Training

Assuming success of efforts described in the previous subsection, the next step in improving both model accuracy (research angle) and therapeutic change (clinical angle) would be to incorporate a fully-fledged HMI/BCI. Specifically, it is as if the model would have learned “all there is to know” about the individual, and so operate irrespective of continuous learning from data input. Assumed here, within the context of finite computational power, is a necessary trade-off: the more data-intensive (and associated processing steps) a HMI/BCI is burdened with as its underlying algorithms are learning, the less it can adapt quickly the XR content. This is especially true for VR (e.g., visual field content generation), and even more so if one is to assume a large deployment of the proposed platform (i.e., hundreds if not thousands of HMI/BCIs requiring not only live-computations, but also learning-serving computations).

From a pragmatic standpoint, actors should be aware of an eventual cut-off point, where each individual HMI/BCI parameters would run independent, adjustment-free. Importantly though, as novel situations can arise (especially in free-range), the collecting and use of these data to continue AI learning is strongly encouraged. This would likely involve implementing a routine for HMI/BCI model updating. Computational-economy-wise, an optimal moment for model learning and update would be when both input data and content generation are minimal, that is, sleep time; if generalized across offenders to a same (e.g., city) area, that would be nighttime.

In parallel of these concerns, progress in ML and DL has further pushed CPsy on the individualized, idiographic, approach, namely, precision psychiatry (Bzdok & Meyer-Lindenberg, 2017; Chen et al., 2022b; Williams et al., 2024). While this approach has its own merits, given the data to be collected under the proposed monitoring opportunities, greater attention will be given to the prospect of forensic digital twins (FDT). A digital twin is, in principle, an exact computational replica, a simulation, of an existing physical system (Batty, 2018), with its algorithms mimicking said system’s multilevel dynamics. The integration of digital twins has already been thought about within a CPS framework (Alam & El Saddik, 2017) and healthcare (Katsoulakis et al., 2024), and this exactitude the twin aims for echoes the previous “all there is to know” about individual offenders. To be clear, a FDT, once made, has no bearing on any feedback the CPS might direct towards the offender. Rather, as the offenders copy, it could be used to modulate a variable, or series of, that simulate the offender's environment, generating in turn a response from the FDT. Two courses can follow: one uses the FDT’s response to predict the offender’s response, or one uses the FDT’s “failure” in mimicking the offender. The former option can inscribe itself in general efforts of causal ML (Feuerriegel et al. 2024) and ML/DL approaches to predict treatment outcome (Chekroud et al., 2021) or reoffending risk. Validation-wise, three angles deserve mention (these angles are closely tied to the data production contexts found in Figure 1). From a research angel, a FDT could be tested in juxtaposition of the related offender, directly testing its validity in this context. From a psychiatric angle, the FDT’s prediction capacity could be contrasted with clinical insight (e.g., a specialist’s prognosis). From a criminological, recidivism angle, the FDT’s prediction capacity can be contrasted with existing forensic predictors (e.g., actuarial risk scales). The failure-oriented option, which can apply for any of the above angles, could benefit from testing various iterations of same-offender FDTs, and since these would not be fully independent from one another, the events or measures in between consecutive FDT iterations could themselves be given special ML or DL treatment for explaining predictive discrepancies. Naturally, an FDT could be itself updated following the same scheme as in the previous paragraph, and in turn, help to the betterment of the proposed XR-themed HMI/BCI (Barricelli & Fogli. 2024).

The same data and models that served in building digital twins could help make ecologically valid artificial patients for a forensic professional's formation; interactive contexts varying in scope and ecologically adapting to the offender's behaviours (e.g., speech content, prosody, gaze direction). Recent initiatives using chatbots with realistic speech options and appearance for formation purposes already exist (e.g., Raiche et al., 2023; Vaidyam et al., 2019). What is advocated here it to move beyond the fixed and predetermined response options of chatbots, towards situationally adapting and personalized response options. There is great potential on this front with LLMs. In parallel, the scope of varying behaviours the artificial agent can modulate would also grow.

3 CYBERSECURITY

An important underlying assumption of what has been presented thus far is the approval given by the regulatory bodies and involved detention institutions, as well as the obtaining of offenders consent whenever applicable. Paramount to these approval status’, one must expect strict protocols and an infrastructure that secures data anonymity, access and transfer (Anand et al., 2006; Khaitan & McCalley, 2015; Sarode et al., 2022; Torous et al., 2021). This involves "traditional" challenges of cybersecurity, which are beyond the scope of the proposed frame. The present section will rather focus on the vulnerability of the human mind in the context of technology usage, with an emphasis on immersive (i.e., presence inducing) XR technologies. The section will conclude with opportunities the same technologies provide in promoting adaptation.

3.1 From Presence to Social Engineering

The phenomenon of presence is best summarized as the feeling and ability to be/do "there", this in reality as well as XR (Riva et al., 2011). Presence is at the core of what can make XR technology useful to simulate the real world in the first place, guiding the immersiveness it strives for (Slater, 2003). It is also a versatile concept with various emphases a clinician or researcher can inquire upon. For instance, a HMI/BCI (forensic) psychiatrist enthusiast could be interested in what causes (or actively maintains): a patient's social inaptitude (ties to social presence; Biocca et al., 2003), paraphilic interests (ties to sexual presence; Brideau-Duquette & Renaud, 2023), and so forth.

However, the relative ease with which presence can be induced also makes it a psychological vulnerability. Akin is the infamous Turing test, which, at its core, implies something successfully convincing a human being it has sentience (Saygin et al., 2000); from "fake world" to "fake being". A marked example is the large leap in progress LLMs, and the often-reported sense that one is interacting with a comprehending entity when prompting such LLM (e.g., Shanahan, 2024). As hinted above, the proposed HMI/BCIs for offenders would capitalize on such intuited impressions, as they would serve presence, and so define the XR generated content (see also Wang et al., 2024a) within the CPS.

With prevention in mind of reoffending, but also first offense, one should consider that we are not equal when facing such "in the wild" Turing tests. A notable example would be of (pre)psychotic individuals, for whom it is arguably expectable that LLM-based applications, existing or to be, will constitute a risk of psychosis triggering. This would be especially so if coupled with easily accessible and unsupervised, and presence-inducing, technologies. In other words, presence while in XR can (potentially) lead to estrangement when in reality (see also Aardema et al., 2010). This is arguably a problem that extends to any interactive platform, as exemplified by problematic social media usage (Sun & Zhang, 2021).

These concerns, generalized beyond psychosis, relate to social engineering. The latter is defined by Wang and colleagues (2020, 2021) as a cyberattack where the perpetrator socially engages in some manner to trick someone into behaving in a certain way that breaches in place cybersecurity measures. Concerns have been raised that affective and cognitive traits could be vulnerabilities to such social engineering, especially if ML is used to perfect cyberattack schemes (Wang et al., 2020). The main point here: in a context of personal data markets (Spiekermann et al., 2015), and that private interests could gain the same types of measurements as those mentioned above (akin to, say, lingering time on a social media post) with personal XR usage, the same, optimal presence indicative data could be used for social engineering; in other words, use the same ideas elaborated throughout, but for nefarious or unwanted (e.g., marketing) purposes. A case and point would be the instillation of so-called dark patterns, this, via technologies of various immersiveness quality, but efficient in said instillation as immersiveness grows (Wang et al., 2024b), presumably because of presence.

We would extend the earlier definition of social engineering, so it encompasses more of its original, top-down normative effort (Duff, 2005). Rather than considering political approach and ideology, we would define said top-down influence: the controlling actor (e.g., hacker, service provider) actively modulates the technological medium to psychologically (i.e., cognitively, affectively or behaviourally) influence an individual without their knowledge or consent. In fact, the FPsy approach advocated for here largely fits this extended definition, with the crucial distinction that offenders would be both informed about the general aims of the CPS, and provide consent.

3.2 Adaptation Building, Towards Autonomy

A necessary goal for any psychiatric intervention is to promote maximal autonomy of the individual. This is also true in forensic-related settings, with the equally prominent concern of the offender's and others safety. Merging the two involves making psychiatric offenders more autonomous in ensuring the safety of themselves and others. The previous subsection emphasized the importance of surveilling for negative impacts of immersive technologies and social engineering, but as the earlier sections would hint, the poison can be part of the cure: mechanisms that facilitate social engineering might also facilitate trait resilience building.

The proposed CPS-XR architecture has much in common with biofeedback approaches, as in both cases, continuous physiological or behavioural measurements take part in influencing some feedback to be perceived by the individual. Assuming a genuine willingness to change on the offender's part, the same data that successfully predicts a near-imminent issue (e.g., aggressive outburst, behavioural disorganisation) could be used to promote situation awareness (Alsamhi et al., 2024; Endsley, 1995), an important step in de-escalation and in some cases, long-term problematic pattern discontinuation.

This assisted situational awareness could serve in both institutionalized and free-range monitoring conditions. In the former, one could envision its common use by the mental health professional and the offender in a therapeutic setting, allowing in-the-moment flexibility, as said professional can adapt the sessions therapeutic target. This would be especially relevant for mindfulness-based interventions (Chandrasiri et al., 2020), and more generally, as a solid base for the learning of de-escalation/reorienting, self-regulation strategies. Using XR has the additional value to lessen abstraction in forming or applying said strategies. For instance, feedforward cues, perceptually salient and intuitive instructions about what could be done in the XR-related environment (Muresan et al., 2023). In a free-range setting, previously learned strategies can be put to the test. In collaboration with the offender, who can give subjective impressions, as well as with objective criteria of de-escalation/reorienting, the continued input of behavioural or physiological data could serve in further modelling both strategy success and failure, and their respective predictors.

4 CONCLUSION AND FUTURE DIRECTIONS

The advent in recent years of both conceptual developments in psychiatry and access to quality XR technologies converge to stimulating clinical and research possibilities. Presented here was a CPS general configuration to better equip FPsy in capitalizing on these possibilities, and how doing so also relates to human-centered cybersecurity features, present and future.

Still, pending issues little to not addressed here require consideration. Ethical concerns relating to offenders' consent, specifically, it being genuine as opposed to pressured, should be examined; one should note that any research or psychotherapeutic intervention within a forensic setting has that exact issue, as the offender, facing the judicial system, is imposed a lifestyle and routine, in which, here, the proposed CPS would happen to inscribe itself in.

To our knowledge, no implementation akin to what has been proposed was ever attempted in forensic settings. Perhaps such implementing is not realistic in all jurisdictions. Where possible, any such attempts at establishing a forensic CPS should self-monitor its incremental efforts, so as to give insight in the challenges ahead. At the crossing of logistical and ethical concerns overreach, the proposed CPS scheme might be better implemented in successive steps. We propose the following such steps as a general path to the complete CPS: institutionalized clinical settings and research, institutionalized offender day-to-day living settings, free-range clinical and research appointments, day-to-day living settings. In between each of these steps, one would consider the same settings with XR integrated to it (e.g., institutionalized day-to-day would transition to institutionalized day-to-day complemented with XR technology).

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