Passive Monitoring of Mental Health Status in the Criminal Forensic Population

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Current approaches to monitoring patients' mental status rely heavily on self-reported symptomatology, clinician observation, and self-rated symptom scales. The limitations inherent in these methodologies have implications for the accuracy of diagnosis, treatment planning, and prognosis. Certain populations are particularly affected by these limitations because of their unique situations, including criminal forensic patients, who have a history of both criminal behavior and mental disorder, and experience increased stigma and restrictions in their access to mental health care. This population may benefit particularly from recent developments in technology and the growing use of mobile devices and sensors to collect behavioral information via passive monitoring. These technologies offer objective parameters that correlate with mental health status and create an opportunity to use Big Data and machine learning to refine diagnosis and predict behavior in a way that represents a marked shift from current practices. This article reviews the approaches to and limitations of psychiatric assessment and contrasts this with the promise of these new technologies. It then discusses the ethics concerns associated with these technologies and explores their potential relevance to criminal forensic psychiatry and the broader implications they carry for health and criminal justice policy.

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Current practice for monitoring a patient's mental status relies broadly on patient self-report and physician observation during clinical interviews.[1] The limitations inherent in these methodologies can curtail the capacity of psychiatry to assess and monitor patients, with implications for diagnosis, treatment planning, and prognosis.[2] These problems may be particularly prevalent in criminal forensic populations, given the incentives they may have to not report accurately on their symptoms and behavior. The introduction of new technologies involving passive electronic monitoring and the use of new information-processing models hold the promise of improving the ability of mental health clinicians to assess their patients' mental states, with clear applications in forensic mental health. At the same time, these technologies may create new clinical and ethics challenges that clinicians will need to address.

The subjective nature of self-report and clinical interview strategies creates barriers in evaluation accuracy due to inter-related patient, clinician, and dyadic factors. Accuracy of patients' self-reports can be impaired by intentional misreporting or as a byproduct of the disease process. Many mental disorders are characterized by a lack of insight into the very symptoms for which patients are being evaluated. Similarly, recall bias, whether due to cognitive distortions inherent in the disease process, response to contextual cues, or the limits of human memory, compound this problem. Moreover, people tend to rely on their momentary affective states to assess the quality of their lives in general, which becomes particularly meaningful when evaluating states of extreme affect, such as depression or mania.[3-5] Finally, the social desirability of the behavior in question may distort reporting as people engage in impression management, driven by their own personality traits or by fear of stigma and repercussions associated with honest disclosure.[6]

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Clinician-related factors also contribute to the limitations on accuracy associated with the current approaches to gathering mental health data, including the skill and expertise of the evaluator. Practical challenges, such as heavy patient loads that leave little time for careful assessment and concerns about alienating the patient by intensive probing, may also come into play. Moreover, the interaction between the patient and the clinician can create further barriers to accuracy, including the distorting effects of transference (e.g., patients wanting to impress the clinician with how well, or how poorly, they are doing) and countertransference (e.g., clinician hostility toward a difficult patient impeding careful inquiry). Patients and clinicians may have differing treatment goals, which may strain the therapeutic alliance and compromise the accuracy of the assessment. Taken together, these patient, clinician, and dyadic factors have the potential to distort the quality of the data used for assessment and monitoring to formulate diagnosis, plan treatment, and evaluate prognosis.

Recent advances in technology have positioned both clinicians and researchers to better assess patients using data generated via passive monitoring (described in detail below) and employing Big Data approaches to analysis. Big Data has been defined as the "union over a range of tools and disciplines involved in collecting, storing, and analyzing large amounts of data originating from observing the interaction between users and devices (e.g., smartphones)" (Ref. 1, p 407). Big Data applications focus on either revealing previously unknown trends (i.e., data mining) or uncovering new qualities about known entities (i.e., machine learning). Although passive monitoring and utilization of Big Data in psychiatry is relatively early in its development, there nevertheless have been a variety of applications that hint at a wide range of possibilities of both data types and monitoring formats. A recent systematic review by Cornet and Holden[7] of passive sensing of mental well-being found 35 empirical papers that represented a range of individuals, including those with bipolar disorder, schizophrenia, depression, and the general population. The authors reported benefits of passive sensing that "included accurately detecting changes in status, behavior change through feedback, and increased accountability in participants," and observed utilization of an array of smartphone sensors to achieve these goals, "most frequently capturing accelerometry, location, audio, and usage data" (Ref. 7, p 120). Big Data approaches will enhance the datasets available to clinicians, but decisions regarding patient management will still be based on clinical judgment. One group for which these approaches may be particularly relevant is criminal forensic patients.

Limits of Clinical Assessment

Criminal forensic patients have histories of criminal behavior and mental illness. Compared with civil psychiatric patients, this population has an overrepresentation of severe mental illness, the potential for increased sensitivity to stigma and fear of repercussions associated with honest disclosure (given that their evaluations could lead to incarceration or hospitalization in maximum security settings), and disproportionately limited access to skilled clinicians in jails or prisons.[8] Factors affecting their reporting may be bidirectional: fear of stigmatization can potentially lead to under-reporting symptoms; and motivations for secondary gain, whether to obtain specialized services or to avoid criminal responsibility, may potentially lead to over-reporting. In any of these scenarios, evaluees' motivations may lead to inaccurate or filtered data collection. The prevalence of severe mental disorders in people involved with the criminal justice system also means that poor insight may be a significant problem, further compounding the potential inaccuracy of data collected by self-report or clinician interview.[9]

For many individuals, incarceration represents the first interaction with mental health treatment and brings with it an opportunity perhaps not otherwise available because of financial barriers, individual preferences, cultural beliefs, or lack of resources or motivation. Nevertheless, there remain challenges to the delivery of this care that can result in limited access, whether due to logistical barriers or shortages of trained professionals because of fears about working in correctional settings. The stakes associated with inappropriate treatment for this population are doubly high because their status as both mentally ill and criminally involved receives scarce resources from both the mental health and the criminal justice systems.

People with serious mental illness are overrepresented throughout the criminal justice system.[8] The average rate of serious mental illness among individuals in jails, in prisons, on parole, or on probation is 17 percent, which is significantly higher than the general population, estimated at five percent[9-11] Even more concerning is that people with mental illness are more likely to be arrested and have a higher likelihood of recidivism. When released, they are more frequently reincarcerated as a result of violating conditions of probation than as a result of committing a new crime[12-14], and violations are often due to symptoms of their mental disorders.[15] Once incarcerated, jails spend approximately "two to three times more money on adults with mental illness . . . than on those without those needs, yet often do not see improvements to public safety or these individuals' health."[16] This is an evolving crisis an evolving crisis in terms of treatment and societal costs, whether calculated from financial, humanitarian, or safety perspectives.

The need for improving the management of the forensic population is reflected by the development of multiple programs to reduce the number of people with serious mental illness in jails, including assisted outpatient treatment,[17] mental health courts (MHC),[18] crisis intervention teams,[19] other jail diversion programs,[20] and the Stepping Up initiative, which is led by the American Psychiatric Association, the National Association of Counties, and the Council of State Governments.[16] These initiatives, however, continue to rely on standard psychiatric approaches to clinical assessment despite the potential limitations inherent in this process in general and especially for the criminal forensic population. Thus, while these initiatives strive to enhance connections to treatment for persons with mental illness, improve supervision and care coordination in community-based settings, and reduce recidivism, there remains the potential to improve their fundamental approaches. These programs may represent an area in which approaches utilizing passive monitoring and Big Data may be especially appropriate and uniquely beneficial.

Technology and Passive Monitoring

Smartphone applications (apps) for use by mental health providers have proliferated in the last several years, offering novel capacities to monitor patients' mental states. Several examples may illustrate the spectrum of behavioral analysis possible with the new technologies. The University of Michigan is currently investigating the use of an app called PRIORI, which runs in the background of participants' phones and monitors speech through the microphone in an attempt to detect symptoms of mania in patients with bipolar affective disorder. Specifically, this approach uses "a smartphone app to record changes in acoustic features of speech (volume, speed, and pitch) as well as patterns of daily smartphone use among patients to predict impending mood changes" (Ref. 21). Similarly, Massachusetts General Hospital, in partnership with Cogito, has created the Companion app, which uses voice analysis in conjunction with social interaction data (including texting frequency and location tracking) to provide real-time mood feedback to patients with major depressive disorder and bipolar affective disorder.[22] Dartmouth College is piloting an app called Crosscheck, which uses multiple datasets, including global positioning data; accelerometer, microphone, light, and sound sensors; and weekly mood checks to create a "relapse signature" in patients with schizophrenia, who then receive a push notification from the app if their signature reappears.[23]

Other studies have explored how to use behavioral data to improve disease insight. For example, MONARCA 2.0 "records subjective and objective data from patients suffering from bipolar disorders, processes this and informs both the patient and clinicians on the importance of the different data items according to the patient's mood" (Ref. 24, p 133). The goal of MONARCA 2.0 is to provide patients with "increased insight into the parameters influencing the nature of their disease" (Ref. 24, p 133). The investigators accomplished this goal by exploring which factors (including objective and self-reported factors) had the greatest impact on mood. Objective data included passively collected measurements of social activity, physical activity, mobility, and phone usage, whereas self-reported data included mood, irritability, sleep, medication adherence, changes in medication, activity level, stress level, cognitive problems, alcohol intake, and presence of warning signs. The investigators built models using machine-learning techniques trained on either the objective data or a combination dataset that used objective and subjective parameters for each patient and compared the relative abilities of these models to correlate with mood ratings and to forecast future moods. Models trained on objective datasets alone provided better forecasts of future moods than those built with data using added subjective information.

These applications share many common features, including that they are unobtrusive to the user; with few exceptions, no unique interaction with the device is required to generate useful data. This approach has the dual benefit of minimizing burden to the patient, which could improve long-term compliance, and bypassing several of the dominant sources of bias that plague current methods for collecting psychiatric data, such as impression management, recall bias, cognitive distortions, and lack of insight. Furthermore, these approaches generate data continuously, which provides behavioral information previously inaccessible and with much finer granularity than the information available at the fixed time intervals of doctor–patient appointments.

Definitive judgments about the validity and utility of data collected by these applications cannot yet be made, but early data are promising. For example, Mota *et al.*[25] used voice analysis to differentiate speech patterns related to psychosis. They recorded and analyzed interviews with schizophrenic, manic, and healthy subjects, generating speech graphs.[25] Even when verbosity was discounted, classifiers based on speech graph measures could distinguish schizophrenia from mania with up to 93.8 percent sensitivity and 93.7 percent specificity, using Structured Clinical Interview ratings as the gold standard.[25,26] These findings stand in marked contrast to the sensitivity and specificity achieved in the same study using two standard psychiatric scales, the Brief Psychiatric Rating Scale and the Positive and Negative Syndrome Scale, which reached only 62.5 percent sensitivity and specificity. These results were echoed in another study in which a machine-learning algorithm was applied over 2.5 years to free-text samples from 34 adolescents at high risk for psychosis.[27] The investigators reported that the algorithm identified the five participants who later developed psychosis with 100 percent accuracy, again surpassing clinical prediction.[27] A final example involved data collection over a 10-month period on bipolar patients in a psychiatric hospital in Austria using an "application based on smartphone behavior and activity monitoring" to create data "usable as an 'objective' measurement that helps detect state changes to guarantee the availability of in-time treatment" (Ref. 28, p 142). This study compared evaluations of mood state changes using combined sensor features (including phone call, sound, voice, and movement features) to evaluations using standard scales (i.e., Hamilton Depression Scale and Young Mania Rating Scale). The results showed that, when all sensor modalities were fused, the precision of state change detection was 97 percent, suggesting almost perfect accuracy and implying that this approach might reliably detect early warning signs of pending state changes in bipolar disorder.

These results suggest not only the potential to provide psychiatrists with additional information that captures change and improves prediction but also to enhance the accuracy of diagnosis. For example, if passive monitoring of a depressed patient also reveals a pattern of decreased need for sleep accompanied by changes in behavior or speech patterns for brief periods of time, it may alert the psychiatrist to consider instead a bipolar diagnosis. Real-time monitoring may also allow for parsing the timeline of psychotic versus affective symptoms and assist a clinician in distinguishing schizoaffective disorder from an affective disorder with psychotic features. Both examples would have meaningful implications for treatment and represent an important potential benefit of this technology.

Taken together, these findings suggest that these approaches may become important tools to assist psychiatric clinicians in capturing real-time changes that could represent treatment responses or signs of decompensation, and to provide opportunities for earlier intervention. Not surprisingly, however, such a shift to passive information gathering raises significant ethics concerns, as it negates patients' abilities to choose what to disclose and when to disclose it, undermining their power to withhold information selectively about symptoms or behaviors. From one perspective, these concerns can be viewed as a side effect of a new treatment and thus part of the "proud tradition of balancing risks and benefits on a case-by-case basis" (Ref. 1, p 410). Markowetz *et al.*[1] argue that these new methodologies hold great promise for improving treatment of mental disease, and that it would be equally unethical to deny their usage globally because of concerns for misuse were the information to fall into the wrong hands.[1] Whether patients will share this perspective is unclear, especially in populations that are mandated to receive treatment rather than seeking it on their own. In the next section we consider the use of passive monitoring for criminal forensic patients.

Applications for Forensic Populations

Persons Found Not Guilty by Reason of Insanity

One population for which these approaches may be attractive is persons who have been adjudicated not guilty by reason of insanity (NGRI). Although terminology differs across jurisdictions, these are people who have committed an illegal act but were found not to be criminally responsible for their behavior due to mental illness. Perhaps because of the causal nexus between mental illness and criminal behavior in this population, many members of the public fear recidivistic violence by insanity acquittees after their release. These concerns have been manifest in statutory revisions to the insanity defense itself (e.g., its abolition in some U.S. states, narrowing of its legal standard in others, and changes to the standard and burden of proof), as well as in reform of the management of acquittees postadjudication.[29] In response to these concerns, several U.S. jurisdictions have created programs to monitor insanity acquittees after release into the community to ensure compliance with release conditions (including participating in treatment) and to initiate rapid rehospitalization in case of decompensation. This approach has been successful in reducing arrest rates, including for violent offenses, and generally supports the perception that closer community supervision contributes to reduced recidivism.[30-33] Moreover, data from New York State's reform of its NGRI posttrial procedures suggest that closer community supervision can lead to an increase in insanity verdicts, perhaps because of greater comfort on the part of prosecutors and judges with the consequences of an NGRI finding.[34]

New methods of continuous monitoring and real-time information using passively collected, objective information to create "electronic biomarkers" of relapse may have particular appeal for the management of the NGRI population. Such strategies bypass the limitations of approaches that rely on self-report and clinical interview of insanity acquittees, who, when faced with the prospect of rehospitalization, may have strong motives not to be forthcoming about their symptoms and behaviors. Because of the passive nature of this type of monitoring, variables important to evaluating a change in clinical status (such as sleep patterns, geolocation data, speech analysis, or activity) can be assessed even if the individual tries to limit cell phone use. Given the forensic context, if individuals were required to carry their phones with them (and leave them on) at all times, it would not be easy to avoid supplying the information needed to monitor their symptom states. To the extent that passive monitoring increases confidence in clinicians' abilities to detect incipient decompensation, it could lead to earlier release from forensic hospitals to the community. Once in the community, the improved ability to track significant changes in acquittees' mental states and earlier intervention may help avoid reinstitutionalization. Thus, more intensive monitoring could lead to a net gain in individual liberty for insanity acquittees and greater safety for the public.

Defendants Under the Jurisdiction of MHCs

Another population for which these technologies may be particularly appropriate is defendants who have been diverted by the legal system into specialty MHCs, which are programs that "steer willing and eligible mentally ill offenders away from incarceration and toward court-supervised treatment . . . with the goals of reducing jail overcrowding and recidivism and improving offenders' quality of life" (Ref. 35, p 207). The values behind MHCs stem from the principle of therapeutic jurisprudence, the belief that legal practices and the law can be used to "promote the physical and psychological well-being" of those subject to its proceedings (Ref. 36, p 16). Based on the drug court model, MHCs aim to reduce recidivism by addressing the need for treatment in this specific population and embracing a therapeutic and supportive rather than an adversarial and punitive approach. Steadman *et al.* have suggested that one of the characteristics of a MHC is that "appropriate monitoring occurs under court aegis with possible criminal sanctions for noncompliance, such as reinstituting charges or sentences" (Ref. 37, p 458). Current research on the use of MHCs is promising in suggesting an ability to lower post-MHC arrest rates and jail time compared with arrest rates and jail time for defendants who go through the usual criminal justice process.[38-40]

Defendants diverted to MHCs thus represent another criminal forensic population in which passive monitoring could have an important role; positioned to collect information relevant to the individuals' clinical status continuously and objectively, these strategies might represent yet another tool to encourage diversion of mentally ill defendants from the correctional system and into a system more appropriate to their needs. This shift would have the added benefit of alleviating the burden of overcrowding in jails and prisons, now struggling with large numbers of persons with mental illness. As with insanity acquittees, an increased ability to monitor these defendants may raise the level of comfort associated with using a specialty court rather than the traditional resort to incarceration. This would be especially likely if passive monitoring technologies are demonstrated to be effective in helping MHCs step in with appropriate interventions in a timely manner. Although the use of this technology by MHCs might lead some defendants to refuse participation, experience to date suggests that, when the alternative is jail or prison, this number is not likely to be substantial (e.g., in one major study, refusal rates were less than 5% in six of seven MHCs without monitoring technology examined).[41]

This is by no means a complete list of the criminal forensic populations for which passive monitoring technology may be used. Other groups include offenders with mental illness who are on probation or parole, sex offenders committed to outpatient treatment, and persons found incompetent to stand trial who are being evaluated and restored to competence in the community. The use of such approaches in pretrial forensic evaluations will, however, raise Fifth and Sixth Amendment concerns that may limit their use to defendants who agree to be monitored. Additionally, it is important to remember that passive monitoring to assess changes in mental state is primarily being developed as a tool for the delivery of clinical care.[42,43] To the extent that these technologies are used clinically for the general psychiatric patient population, they will generate additional information that could be incorporated into forensic evaluations if some of these patients become entangled with the criminal justice system. For this reason, the ethical utilization and legal admissibility of such information requires further exploration.

Ethics and Legal Considerations

The methodological shift in the collection of psychiatric health information represented by the development of passive monitoring and machine learning has many potential advantages. It is not, however, without conceivable risks. The undeniable reality is that continuous monitoring and collection of symptom and behavioral information, irrespective of input from the user, constitutes a substantial intrusion on privacy. Such intrusive monitoring may be justified by a determination of guilt, a finding of nonresponsibility, or, as in the case of MHCs, by the voluntary acquiescence of a defendant interested in avoiding prosecution or incarceration. Nonetheless, unless passive monitoring can be demonstrated to improve one or more socially desirable outcomes, which remains to be demonstrated in a criminal forensic population, even these justifications will be inadequate.

With neither courts nor clinicians accustomed to dealing with data at the level of granularity offered by passive monitoring, responses will not necessarily be appropriate. Minor fluctuations in mental state that might previously have gone undetected may now trigger rehospitalization or reincarceration if decision-making protocols are not revised adequately to reflect changes in the level of sensitivity of collected data. Clinicians and judges may need to recalibrate the degree of symptom recurrence at which they intervene. Furthermore, they will need to avoid conflation of psychiatric decompensation with treatment noncompliance. Although poor adherence is one cause of symptomatic recurrence, other causes include natural fluctuations of symptoms, progressive disease processes, and responses to increased stress from external circumstances. Of course, this concern already exists with current approaches to managing acquittees on conditional release as well as defendants diverted to MHCs.[44] Nevertheless, care must be taken to ensure that the increased ability to monitor changes in psychiatric states is not misused and that the data are interpreted correctly and managed accordingly by courts and clinicians alike. The ability to do this competently may require additional training and a commitment to monitor the data generated on an ongoing basis, both of which may affect clinicians' comfort with accepting criminal forensic outpatients who are subject to passive monitoring. The comfort level and logistics of how best to approach this type of monitoring will likely evolve as electronic devices are more widely used for this purpose in the general psychiatric population. It has already been suggested that professional organizations such as the American Psychiatric Association consider developing guidelines for incorporating these approaches into current practices, given the push in both private and academic research sectors toward developing mental health applications.[45] Such suggestions could inform the application of the same strategies with the criminal forensic population.

Compulsory monitoring will create a body of data of potential interest to police and prosecutors. It is already common in criminal investigations for police to access suspects' mobile phone records and geolocations. Additional information regarding suspects' speech patterns and activity levels could do more than place a person at the scene of a crime; it could offer strong inferences as to what they were doing there. Moreover, detailed information about a person's mental state could support or defeat a claim of nonresponsibility by virtue of mental illness. Once this information exists, accessing it will be irresistible to law enforcement and prosecutors. This information is likely to be considered nontestimonial by the courts and thus will likely fall outside the bounds of psychotherapist–patient privilege, even if it is being gathered for clinical purposes. Although this information may be afforded some protection by health privacy laws (e.g., the U.S. Health Insurance Portability and Affordability Act, or HIPAA), such statutes typically have exceptions allowing law enforcement access, with or without judicial authorization depending on the circumstances.[46] Arguably, knowing that one is being passively monitored at all times could have a deterrent effect on subsequent criminal behavior, but it may also induce resentment and efforts at evasion. Thus, there may be practical as well as fairness reasons to consider precluding the use of these data in investigation and prosecution of charges unrelated to the ones that led to the monitoring.

An additional consideration relates to circumstances in which offenders with mental illnesses are given the option of passive monitoring or entering or remaining in confinement. Can an offender faced with that choice make an acceptably free decision? According to Wertheimer's influential view of coercion, "threats coerce but offers do not" (Ref. 47, p 244). From this perspective, the utilization of these technologies may best be seen as an offer, not a threat, and hence their utilization is not coercive because the offender is no worse off than his original situation dictates if he chooses not to accept passive monitoring. In regard to the choice conditioning freedom on intensive monitoring of mental state, there is a long tradition in many countries of requiring mental health treatment, of which monitoring is a part, as a reasonable condition of remaining in or returning to the community.[48] For instance, Title 18, § 3563 of the United States Code states, "The court may provide, as further conditions of a sentence of probation . . . that the defendant . . . undergo available medical, psychiatric, or psychological treatment." Additionally, in *U.S. v. Stine*,[49] which examined "whether the requirement of psychological counseling as a condition of probation is an unconstitutional infringement on the appellant's rights of privacy and mentation," it was decided that "courts can impose on a probationer limitations from which other persons are free, if the limitations are reasonably related to rehabilitation and public safety" (Ref. 50, p 490–91). Thus, although the courts did not hold that "a psychological counseling requirement can never be an infringement of a constitutional right of privacy," they did find that "when psychological counseling is reasonably related to the purposes of probation, its imposition is not unconstitutional" (Ref. 49, p 491).

Related to the topic of coercion is capacity for decision-making when monitoring is a condition of release, probation, or parole. Current judicial practice is to evaluate an individual's competency to proceed in general rather than to parse decisional capacity for each component of court proceedings.[51] As a result, for the generally competent defendant, even in the parole setting, it is unlikely that courts would inquire specifically into competence to consent to the use of monitoring technologies. Rather, defendants or parolees who are deemed generally competent will likely be considered competent to make all choices relevant to accepting or rejecting the terms of their sentence or release. Thus, the competent defendant, insanity acquittee, or prisoner will have the option of accepting or declining the conditions attached to release. This choice inevitably will be influenced by the consequences of potential refusal (i.e., initial or continued incarceration). Such choices will, therefore, never be completely unconstrained. To the extent that declining passive monitoring does not leave individuals in a state worse than their original situation would dictate, however, it remains best conceptualized as an offer rather than a threat for the competent individual.[47]

Finally, we note that the use of passive monitoring approaches and automated analysis of the resulting data, as in machine learning, may raise questions of admissibility in legal proceedings. Like other evidence based on new technologies, it may be susceptible to challenge on the grounds that it fails to meet the evidentiary standards of the jurisdiction, whether based on *Frye*'s[52] general acceptance test or *Daubert*'s[53] more flexible standard of reliability. To the extent that passive monitoring is premised on voluntary acceptance of the technology, such as when it is a condition for release by a MHC or a parole board, the person being monitored may be deemed to have waived objections to the use of the resulting information in court. Whether other legal obstacles to the use of evidence from passive monitoring develop remains to be determined.

Additional Areas for Future Research

Passive monitoring technologies might also come to play a role in improving risk assessment of criminal forensic populations. With the ability to apply machine learning to data collected over the course of a patient's treatment, new ways of predicting future trajectories based on past behaviors and present conditions may become apparent. In addition, given that some violence risk assessment instruments, like the HCR-20, version 3,[54] include response to treatment supervision as a relevant variable, continuous passive monitoring may provide a new and more complete basis on which that determination can be based. Additionally, recent literature in risk assessment and prediction has pointed to the need for evaluating changes in risk status over time to better conceptualize an individual's risk and to target treatment more effectively.[55] For example, it has been suggested that the measurement of change in dynamic risk factors may better facilitate interventions, and that tracking fluctuations in these dynamic factors may improve prediction of violence and rehospitalization.[56-59] More research will be needed to evaluate whether data from passive monitoring improves current risk-assessment paradigms. It ought to be kept in mind, however, that, unlike current risk-assessment tools, which are actuarial in nature, passive monitoring and machine learning hold the prospect of risk assessment that is truly individualized based on a given patient's pattern of behavior.

When decisions need to be made about returning forensic patients to the community (e.g., insanity acquittees), clinicians are often left to rely on clinical judgments of uncertain validity. Passive monitoring while a patient is still in the forensic hospital could generate much finer-grained data regarding the patient's clinical state and its stability. Systematic follow-up to determine the predictive value of such data could provide an additional source of objective information about readiness for discharge. Additionally, if these devices were used by patients while they were still institutionalized, they could create a monitoring algorithm that was highly individualized to the patient and suitable for transition to the community setting. Although there are challenges associated with the provision of institution-provided smartphones to patients in the inpatient setting, including both privacy and tolerability, studies in community psychiatric hospitals suggest mobile sensing is both feasible and acceptable in these contexts.[60] Use in forensic facilities may be met with resistance and may not always be feasible. Privacy and security concerns can be addressed, in part, by disabling functions and restricting communication capacities other than those required for monitoring. Research on the potential for calibrating these applications for a particular person prior to release holds promise for improving clinical decision-making both in and out of the hospital.

Another potential area in which passive monitoring might play a role is in the assessment of malingering within the criminal forensic population. To the extent that malingering involves deviations from characteristic patterns of illness, it is possible that machine learning may be uniquely poised to identify such divergences. One study thus far has shown that such an algorithm was able to detect individuals feigning depressive symptoms with up to 96 percent accuracy.[61] Whether this degree of accuracy remains when applied to passive monitoring without eliciting specific symptoms has yet to be explored. One hypothetical advantage over current clinical practices, however, may be the continuous access to data collection that passive monitoring provides because even the most sophisticated of feigners may have lapses in stamina, and such lapses may be more likely to be observed outside of traditional settings.

Conclusion

For more than a century, the primary approach to collecting information about a patient's mental status has rested heavily on self-report and clinical interviews. For the reasons discussed throughout this article, certain populations are particularly vulnerable to the limitations of these approaches and are uniquely poised to benefit from a change in current practices. The criminal forensic population, which stands at the intersection of mental health and criminal justice, is one such group. New technologies involving passive monitoring and machine learning, which capture the behaviors of users and provide objective data relating to their mental states, have shown early promise in providing new approaches to assessing patients' clinical status. The application of these technologies to the clinical forensic population warrants consideration of ethics and careful evaluation of the risks and benefits inherent in this potentially intrusive approach. Whether the opportunity for closer monitoring in this manner leads to a relative increase in freedom for mentally ill offenders, similar to the impact of some postrelease supervision strategies in the past, remains to be seen. The potential for decreased recidivism and fewer hospital or jail days would have significant implications for community safety, health care and correctional costs, and civil liberties. The legal and societal consequences of Big Data are far from being understood at this time and will likely evolve over the years to come. Careful thought will need to be given to the appropriate use of collected information and to fail-safe strategies that must be put in place to avoid misuse. Notwithstanding the need for a thoughtful approach, the role of new passive monitoring technologies and machine learning in mental health as applied to the clinical forensic population in particular offers a number of potential advantages and is deserving of further exploration.

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