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CravAlert®: A machine learning and digital phenotype platform for sud recovery monitoring

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Abstract

Background: Substance use disorders (SUDs), particularly opioid use disorder (OUD), remain a leading cause of mortality in the United States, with West Virginia bearing one of the highest overdose death rates nationally. Continuous monitoring of physiological precursors to relapse — including autonomic dysregulation, drug cravings, anxiety, and chronic pain exacerbation — represents a high-value but underutilized intervention target.

Objective: This study reports outcomes from a 100-participant prospective pilot of the CravAlert® program — an integrated wearable biosensor, cloud-based deep auto-encoder machine learning, remote patient monitoring (RPM), and just-in-time Peer Recovery Support Specialist (PRSS) intervention system that generates a unique digital phenotype for each patient, deployed across West Virginia Region 2.

Methods: One hundred individuals in early SUD recovery were enrolled across five community recovery and clinical sites in WV Region 2 (mean age 40; 63% female). Participants were monitored continuously via the VivaLink® VV330 FDA-cleared wearable biopatch, which streamed physiological data (HR, HRV, RR, skin temperature, GPS) to the VeeOne Health® deep auto-encoder machine learning analytics platform trained on over 1.2 million tagged data points. Condition-specific alerts triggered real-time PRSS interventions. Alert distributions, clinical outcomes at 3 and 6 months, and user experience survey results were analyzed.

Results: A total of 616 alerts were generated across the cohort. Anxiety and stress accounted for 398 alerts (64.6%), drug cravings 94 (15.3%), major depression 44 (7.1%), false positives 40 (6.5%), chronic pain exacerbation 22 (3.6%), relapses 14 (2.3%), and sleep apnea 4 (0.6%). At 3 months, CravAlert® participants demonstrated a relapse rate of 2% vs. 60% national average, and MAT retention of 74.5% vs. 46.2% national average. At 6 months, relapse rate remained 5% vs. 85% nationally, and MAT retention was 69.2% vs. 29% nationally. User experience surveys revealed 91% peer recommendation and 79% reported sense of safety.

Conclusions: CravAlert® demonstrates compelling preliminary clinical efficacy as a technology-augmented, peer-centered recovery support platform, with outcomes substantially superior to national averages across relapse prevention, justice involvement reduction, and MAT retention at both 3- and 6-month follow-up. Scaling through Medicaid RPM reimbursement pathways and multi-device compatibility is recommended as a priority.

Keywords: Wearable biosensors, remote patient monitoring, peer recovery support, substance use disorder, opioid use disorder, CravAlert, deep auto-encoder, machine learning, digital phenotyping, relapse prevention, mental health comorbidity, behavioral health, West Virginia

Introduction

Substance use disorders (SUDs), including opioid use disorder (OUD), represent one of the most pressing public health crises in the United States. West Virginia has maintained among the highest age-adjusted drug overdose mortality rates in the nation for over a decade, driven by geographic isolation, poverty, limited healthcare infrastructure, and high rates of poly-substance use [13]. The eight counties comprising WV Region 2 — Berkeley, Grant, Hampshire, Hardy, Jefferson, Mineral, Morgan, and Pendleton — reflect these layered challenges in concentrated form.

The transition from residential treatment, incarceration, or drug court to community-based recovery is one of the highest-risk periods in the SUD trajectory. Relapses during this window are frequently preceded by a recognizable sequence of physiological and psychological precursors: escalating drug cravings, autonomic dysregulation, anxiety, depression, chronic pain exacerbation, and altered behavioral patterns [9, 6]. If these signals can be detected continuously and in real time, clinicians and peer support specialists can intervene before a relapse occurs — a paradigm shift from reactive crisis response to proactive recovery support.

The CravAlert® program was co-developed by Potomac Highlands Guild, Inc. (PHG), a behavioral health organization serving WV Region 2, and VeeOne Health®, a virtual care technology company specializing in RPM and machine learning-based clinical analytics. The system integrates the VivaLink® VV330 FDA-cleared wearable cardiac biopatch with a cloud-based deep auto-encoder machine learning platform and a structured Peer Recovery Support Specialist (PRSS) intervention protocol. The CravAlert® platform is also compatible with a range of consumer-grade wearables including Fitbit, Oura Ring, Whoop Strap, Empatica E4, and Biovotion Strap, enabling flexible deployment across diverse patient populations. This article reports expanded outcomes from a prospective 100-participant pilot study, incorporating alert distribution data, 3- and 6-month clinical outcomes, user experience findings, and machine learning performance metrics.

Background

Physiological Correlates of Relapse and Craving

Wearable biosensor research has consistently demonstrated that autonomic nervous system dysregulation precedes and accompanies relapse events and drug craving episodes. Decreased heart rate variability (HRV) is associated with anxiety, depression, and early-phase cravings, particularly through opioid and stimulant use pathways [3, 6]. Elevated heart rate and respiratory rate are observed during acute stress and stimulant-related relapse. Skin surface temperature changes reflect peripheral vascular responses driven by autonomic activity, while GPS location data provide contextual behavioral intelligence — for instance, proximity to known drug use environments or anomalous immobility patterns consistent with overdose [3, 10]. Together, these parameters compose a multi-dimensional physiological fingerprint amenable to continuous ambulatory monitoring.

Machine Learning and the Deep Auto-Encoder Approach

The VeeOne Health® analytics platform employs a deep auto-encoder architecture for anomaly detection — a neural network approach uniquely suited to high-dimensional sensor data streams including multi-channel EKG, HRV, and concurrent vital signs. The auto-encoder learns compressed representations of normal physiological patterns for each individual, enabling identification of deviations that deviate from the patient-specific baseline — rather than population-level norms. Trained on over 1.2 million tagged physiological data points collected across multiple patients, the model builds condition-specific predictive models for anxiety, drug cravings, depression, and chronic pain exacerbation. This architecture captures complex non-linear relationships within high-dimensional sensor streams and handles the temporal and positional variability inherent in continuous ambulatory monitoring [5].

Personalized Baselines

A defining feature of the CravAlert® analytics architecture is the use of dynamically adjusted, phase-specific personalized baselines. Vital signs such as HR, HRV, and RR are stratified across four activity-posture phases within each 24-hour period: (a) daytime, patient active and upright; (b) daytime, patient inactive but upright; (c) nighttime, lying with no activity; and (d) nighttime, sitting up with no activity. Baselines are continuously updated from the patient's accumulating historical data, and readings falling beyond two standard deviations from the phase-specific baseline are flagged as anomalies. This personalized approach substantially reduces false positive rates relative to population-norm thresholds [8].

The Peer Recovery Support Specialist in the Digital Age

A Peer Recovery Support Specialist (PRSS) is a trained and certified paraprofessional who has lived personal experience with substance use disorder and recovery. Credentialed through state-recognized certification programs, PRSS personnel are equipped to provide non-clinical recovery support services including individual mentoring, recovery coaching, and navigation of treatment and community resources, crisis support, and advocacy. Their defining credential is experiential: having traversed the recovery journey themselves, they bring a depth of empathy, credibility, and relational authenticity to their work that clinical professionals alone cannot replicate. In West Virginia, PRSS certification is administered through the West Virginia Certification Board for Addiction and Prevention Professionals (WVCBAPP), and PRSS services are reimbursable under Medicaid in the state's behavioral health benefit structure.

Peer Recovery Support Specialists bring this lived experience to provide frontline support for individuals navigating early sobriety. Evidence consistently demonstrates their effectiveness in improving treatment retention, reducing relapse rates, and increasing engagement with ancillary services including housing and employment [12]. The CravAlert® model repositions PRSS personnel as data-informed, alert-responsive interventionists — transforming peer support from a scheduled, episodic service into a responsive, physiologically triggered care modality. This just-in-time peer intervention model represents a fundamental innovation in the application of peer support in SUD recovery management.

Materials and Methods

Study Design and Ethics

This prospective observational pilot study was conducted between 2023 and 2025 across five community recovery and clinical sites in West Virginia Region 2. All participants provided written informed consent. The study was reviewed and approved by the Ethics Committee of Potomac Highlands Guild, Inc. All procedures complied with HIPAA and 42 CFR Part 2, the federal confidentiality regulation specific to SUD treatment records. The VeeOne Health® technology platform is compliant with HITRUST CSF, ISO 27001:2013, and URAC accreditation standards. All data were encrypted in transit and at rest, with authorized access only and full audit tracking.

Recruitment Sites

Participants were recruited from five sites spanning WV Region 2 (Figure 1):

- Potomac Highlands Guild, Inc. — 5 Clinical Offices, MAT Program and BUMPS Program
- Berkeley County Recovery Resource Center — Berkeley County
- TPM Recovery Resource Center — Mineral County
- Hampshire County Pathways & Lighthouse Campus — Hampshire County
- Russ Hedrick Recovery Resource Centers — Hampshire & Grant Counties

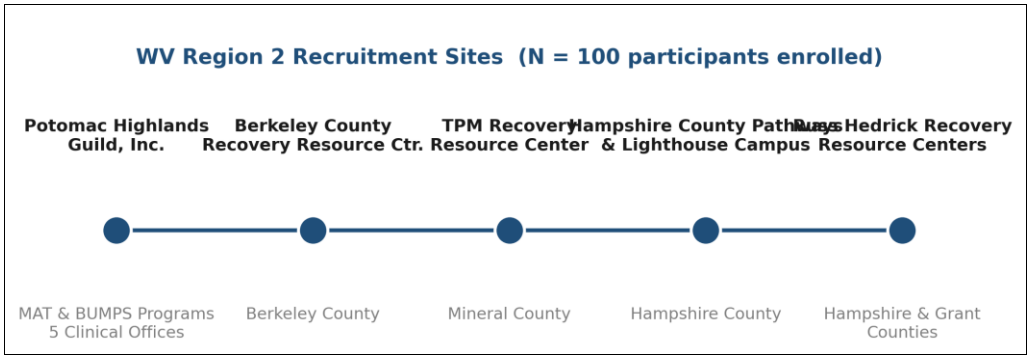

Fig 1: CravAlert® recruitment sites across West Virginia Region 2. Participants (N = 100) were enrolled across five community recovery and clinical sites.

Participants

One hundred participants in early SUD recovery were enrolled. Eligible participants were adults (≥18 years) with a confirmed SUD diagnosis transitioning from residential treatment, incarceration, drug court, or day report centers to community recovery. Participant demographics, derived from the enrollment data presented in Table 1, reflect the diverse and high-acuity profile of the WV Region 2 recovery population.

Table 1: Participant demographics at enrollment (N = 100). Participants may appear in multiple categories.

Category	N
Male	37
Female	63
Average Age (years)	40
Veterans	6
Pregnant / Parenting / Post-partum	22
Justice-Involved	22
LGBTQIA+	7
Ethnic Minority	3

Wearable Technology and Device Compatibility

The primary monitoring device was the FDA-cleared VivaLink® VV330 Continuous ECG Platform (510(k) Number: K191870), a wearable cardiac biopatch capable of continuously streaming ECG rhythm, heart rate, HRV, respiratory rate, skin surface temperature, accelerometer/activity data, and GPS location to a paired mobile device or cloud server. The device is reusable and rechargeable with up to 14 continuous days of monitoring per charge, making it well-suited for ambulatory recovery monitoring.

The CravAlert® platform is additionally compatible with a range of consumer and clinical-grade wearables, enabling flexible deployment

- Fitbit — continuous HR and activity monitoring
- Oura Ring — HRV, sleep, and temperature
- Whoop Strap — HRV, strain, and recovery metrics
- Empatica E4 — EDA, PPG, skin temperature, and accelerometry
- Biovotion Strap — multi-parameter vital signs monitoring

Data Analytics: Deep Auto-Encoder Architecture

The CravAlert® analytics platform, developed by VeeOne Health®, employs a deep auto-encoder neural network architecture for anomaly detection. This approach captures complex non-linear relationships within high-dimensional data streams — including concurrent EKG, HRV, vitals, and sensor channels — and identifies deviations from each patient's personalized physiological baseline. Models were trained on over 1.2 million tagged data points collected from multiple patients across recovery phases and validated using cross-validation techniques with performance metrics including accuracy, precision, recall, F1 score, and Area Under the Curve (AUC). Each predictive model generates a condition-specific risk score; individual scores are synthesized into an overall decompensation risk index via a max-limit function.

PRSS Intervention Protocol

Upon alert generation, the assigned PRSS received a notification via a secure HIPAA-compliant platform and responded through one or more of the following modalities:

- Brief virtual check-in meetings providing immediate support
- Motivational messaging personalized to the participant's recovery stage and preferences
- Coping strategy reminders aligned with pre-identified alternatives (walking, exercise, prayer, music, talking to a friend, cold shower, dancing, meditation)
- Warm referral to licensed behavioral health counselors for moderate-severity events
- Emergency services (EMS) notification for suspected overdose (GPS anomaly + critical vital sign deviations)

PRSS staff also provided wraparound support including assistance with housing, employment, and family reunification through partnerships with Jobs and Hope and the WV Coalition to End Homelessness.

Outcome Measures

Primary outcome measures included: (1) alert type distribution and frequency; (2) relapse rate at 3 and 6 months compared to published national averages; (3) MAT (medication-assisted treatment) retention at 3 and 6 months; (4) arrest/incarceration rate at 3 and 6 months; and (5) user experience survey ratings across five dimensions. Secondary measures included time-of-day alert distribution (24-hour distribution) and time since last meal at point of alert.

Results

Alert Type Distribution

A total of 616 discrete alert events were generated and classified across the 100-participant cohort (Table 2, Figure

2). Anxiety and stress represented the dominant alert category with 398 events (64.6%), consistent with the known high prevalence of anxiety disorders co-occurring with SUD and the role of hyperarousal in craving generation. Drug cravings comprised the second most frequent category at 94 events (15.3%), followed by major depression at 44 events (7.1%). False positive alerts — the majority attributable to occupational physical exertion — totaled 40 events (6.5%). Exacerbation of chronic pain accounted for 22 alerts (3.6%), confirmed or suspected relapses for 14 events (2.3%), and sleep apnea for 4 events (0.6%). The 22 chronic pain exacerbation alerts, though representing 3.6% of the total, carry disproportionate clinical significance in this population, as detailed below.

Table 2: Distribution of CravAlert® alert type categories among 100 participants (N = 616 total alerts). All alerts triggered a Peer Recovery Support Specialist (PRSS) response within the defined service-level window.

Alert Type	Number of Alerts	Percentage (%)
Anxiety and Stress	398	64.6%
Cravings for Drugs	94	15.3%
Major Depression	44	7.1%
False Positive Alerts	40	6.5%
Exacerbation of Chronic Pain	22	3.6%
Relapses (Confirmed/Suspected)	14	2.3%
Sleep Apnea	4	0.6%
TOTAL	616	100.0%

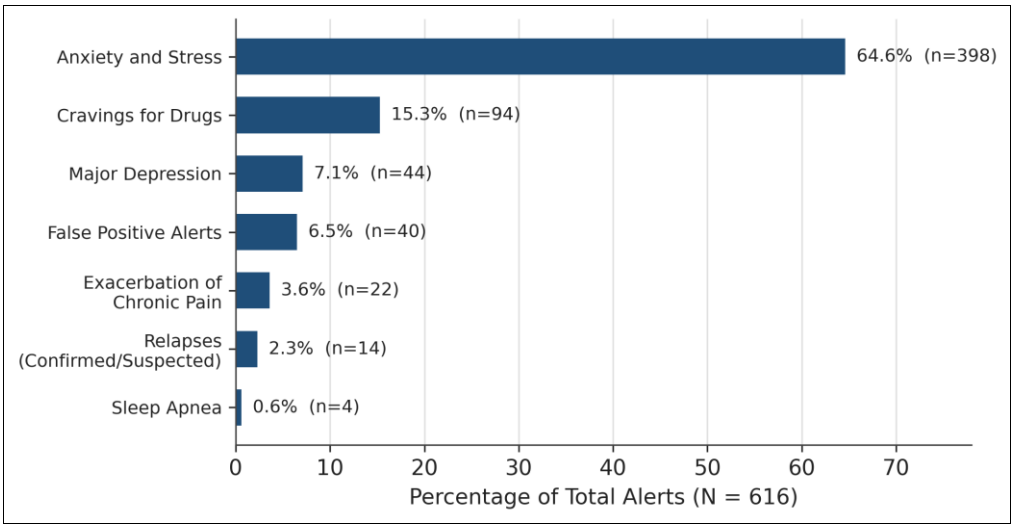

Fig 2: Proportional distribution of CravAlert® alert types (N = 616 total alerts).

Chronic Pain Exacerbation Alerts: An Underrecognized Relapse Driver

The 22 chronic pain exacerbation alerts recorded in this cohort represent more than a discrete alert category — they illuminate a critical and often overlooked dimension of the opioid use disorder crisis in Appalachian West Virginia. For a substantial proportion of individuals with OUD, the pathway into addiction did not begin with recreational drug use. It began with legitimate, medically prescribed opioid analgesia for occupational injuries and chronic musculoskeletal conditions acquired in the industries that define the regional economy: coal mining, logging, and poultry processing plant work.

Decades of underground and surface coal mining across the Appalachian coalfields have produced epidemic rates of spinal compression injuries, herniated discs, degenerative joint disease, and black lung disease — conditions for which opioid analgesics became the standard of care in prior treatment eras. Timber harvesting and logging generate high rates of traumatic musculoskeletal injury, nerve damage, and chronic back pain. Poultry processing, a major employer across several Region 2 counties including Hardy, Grant, and Hampshire, is associated with epidemic rates of repetitive stress injuries, carpal tunnel syndrome, rotator cuff tears, and cervical radiculopathy — including pachydermodactyly (PDD), a disabling acquired digital fibromatosis caused by repetitive mechanical trauma to the proximal interphalangeal joints, documented specifically in poultry workers in West Virginia [14]. Workers who sustained these injuries and were prescribed opioids for pain management over months or years represent a large segment of the OUD population now in recovery across WV Region 2. Their chronic pain did not resolve with their sobriety — and the 22 alerts in this category represent the system detecting, in real time, a relapse signal that conventional recovery programming has historically had no mechanism to identify. The clinical implications of these alerts are discussed further.

Mental Health Alert Burden: Comorbidity of SUD and Psychiatric Conditions

Of the 616 total alerts generated, 398 were classified as anxiety and stress (64.6%) and 44 as major depression (7.1%), yielding a combined mental health alert count of 442 events — representing 71.8% of all alerts recorded in the cohort. This distribution confirms that the predominant physiological signals detected by the CravAlert® system in this population are mental health-related rather than primary substance use events. Every anxiety and depression alert triggered a real-time PRSS response, enabling intervention at the moment of physiological mental health deterioration — before craving escalation or behavioral decompensation could follow. The clinical significance of this finding, including its implications for co-occurring disorder management and expanded platform applications, is addressed in Discussion.

24-Hour Alert Distribution

The 24-hour temporal distribution of alerts revealed two distinct peaks (Figure 3). Peak 1 (blue) represents the

dominant alert cluster spanning late morning to evening hours (approximately 12:00–23:00), reflecting daytime stress, anxiety, craving peaks, and late-evening vulnerability periods. Peak 2 (orange) represents a secondary cluster in the early morning hours, (approximately 01:00–10:30), consistent with early-morning anxiety upon waking, overnight craving episodes, and nocturnal autonomic dysregulation. This bimodal distribution informs optimal PRSS staffing patterns and proactive outreach scheduling.

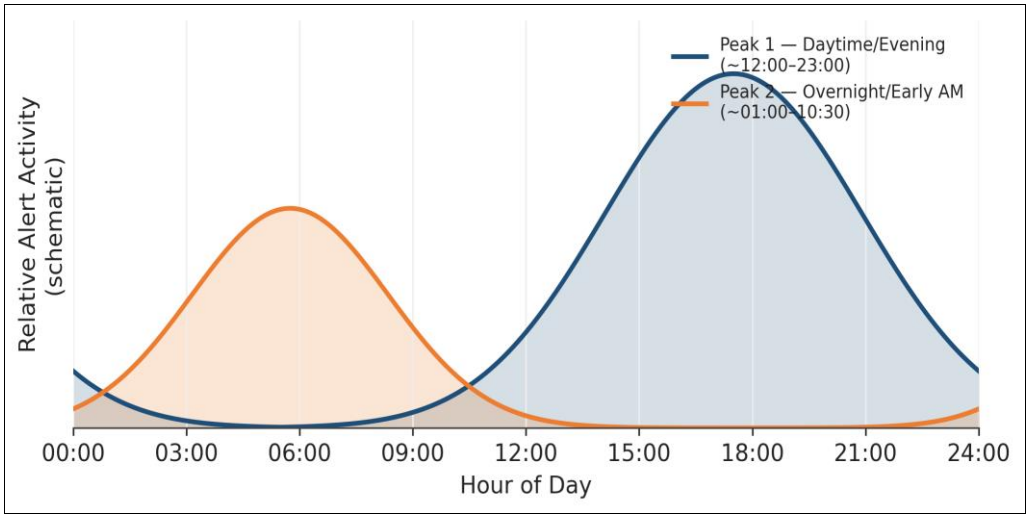

Fig 3: Schematic representation of the bimodal 24-hour alert distribution observed in the CravAlert® cohort. Peak 1 (blue) spans approximately 12:00–23:00 (daytime stress, craving, and evening vulnerability); Peak 2 (orange) spans approximately 01:00–10:30 (overnight craving and early-morning arousal).

Time Since Last Meal Before Alert

Analysis of nutritional context at point of alert generation revealed that the mean time since last meal before an alert was 164.83 minutes (SD = 146.14 minutes; median = 125.00 minutes). The distribution was right-skewed, with the majority, of alerts occurring within 0–300 minutes post-meal (Figure 4). A subset of alerts occurred at 500+ minutes since last food intake, suggesting that prolonged fasting or nutritional dysregulation may be a contributing factor to physiological vulnerability to cravings and anxiety episodes in this population.

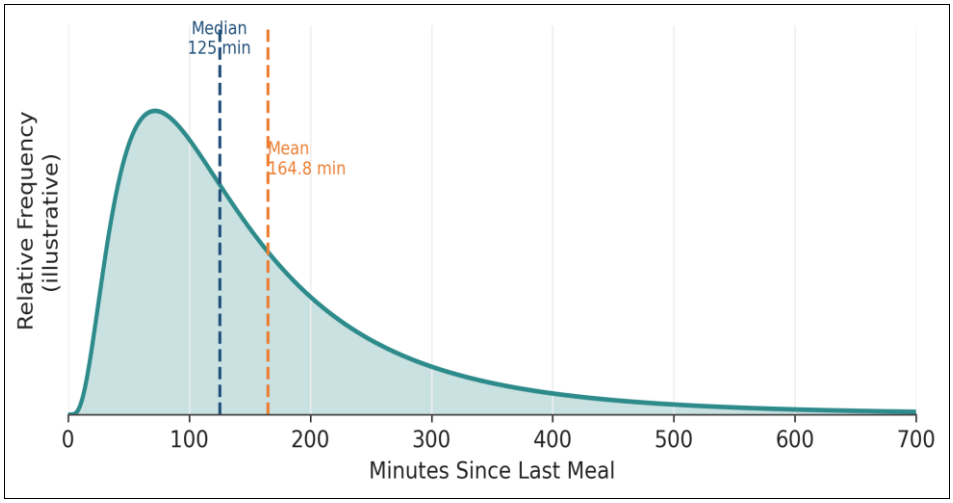

Fig 4: Illustrative right-skewed distribution of time since last meal prior to alert occurrence, based on reported summary statistics (mean = 164.83 minutes; median = 125.00 minutes; SD = 146.14 minutes).

Clinical Outcomes at 3 and 6 Months

Table 3 and Figure 5 present the primary clinical outcomes for CravAlert® participants compared to published national averages at 3-month and 6-month follow-up. The program demonstrated substantially superior outcomes across all three primary measures.

Table 3: CravAlert® clinical outcomes versus national averages at 3 and 6 months. Relapse and arrest rates were substantially lower, and MAT retention substantially higher, than national benchmarks.

Outcome Measure	National Avg. (3 Mo)	CravAlert® (3 Mo)	National Avg. (6 Mo)	CravAlert® (6 Mo)
Relapse Rate	60%	2%	85%	5%
Arrested / Incarcerated	30%	4%	49%	5%
MAT Retention	46.2%	74.5%	29%	69.2%

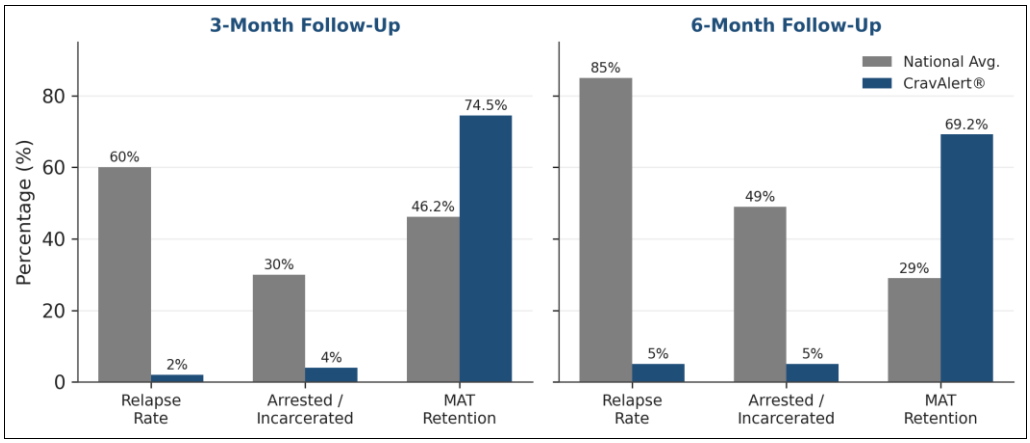

Fig 5: CravAlert® clinical outcomes versus national averages at 3 and 6 months (relapse rate, justice involvement, and MAT retention).

User Experience Survey

A post-participation user experience survey assessed five dimensions of participant satisfaction and perceived program impact (Figure 6). Results demonstrated strong participant endorsement across all domains:

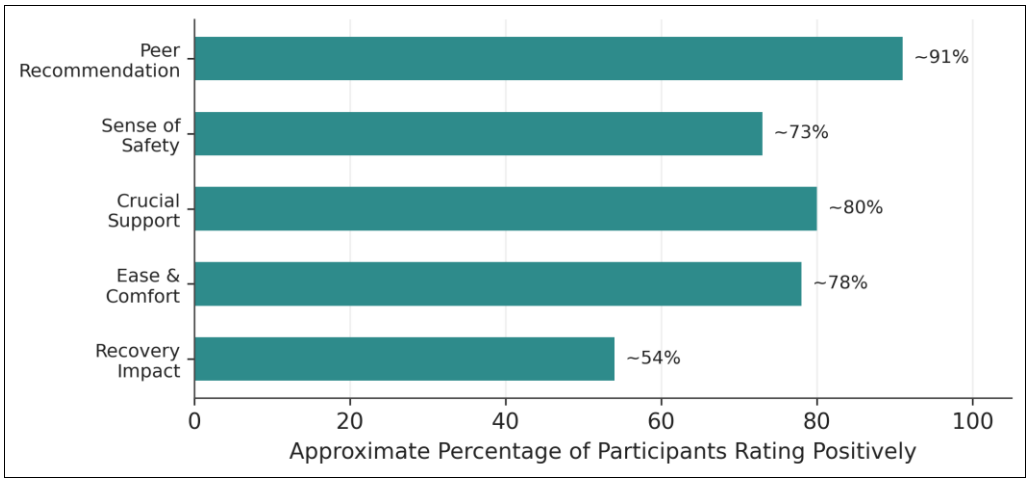

Fig 6: CravAlert® user experience survey findings across five dimensions, reflecting the approximate proportion of participants rating each dimension positively.

Adverse Events

Three participants (3.0%) experienced adverse skin reactions to the biopatch adhesive, ranging from mild contact dermatitis and erythema to a moderate rash with pruritus and burning sensation. One participant discontinued due to a moderate-severity reaction; the remaining two continued with alternative non-latex adhesive patches with symptom resolution. No device-related serious adverse events occurred. No overdose deaths were recorded in the cohort during the study period.

Discussion

Clinical Efficacy: Outcomes Substantially Better Than National Benchmarks

The CravAlert® pilot results present one of the most compelling preliminary outcome profiles yet reported for a technology-augmented SUD recovery support intervention. A relapse rate of 2% at 3 months compared to the national average of 60%, rising modestly to 5% at 6 months versus 85% nationally, represents a clinically and statistically dramatic improvement in early recovery outcomes. Similarly, arrest and incarceration rates of 4% at 3 months and 5% at 6 months — against national averages of 30% and 49% respectively — suggest significant real-world social benefit beyond the clinical domain. MAT retention rates of 74.5% at 3 months and 69.2% at 6 months substantially exceed the national benchmarks of 46.2% and 29%, demonstrating that the CravAlert® infrastructure supports not only behavioral outcomes but pharmacological treatment adherence.

While the absence of a randomized control group precludes definitive causal attribution, the magnitude of observed differences — across multiple independent outcome domains simultaneously — is strongly suggestive of genuine program efficacy rather than selection bias alone.

Chronic Pain as a Persistent and Underrecognized Relapse Signal

The 22 chronic pain exacerbation alerts in this cohort, reported warrant discussion that extends well beyond their numerical weight in the alert distribution. They represent a window into the social and occupational history of addiction in Appalachian West Virginia — a history in which injury, legitimate medical treatment, and physiological dependency converged in the absence of adequate non-opioid pain management alternatives. The pathway from occupational injury to opioid prescription to dependency to OUD is not a story of moral failure; it is a predictable clinical trajectory that unfolded across thousands of lives in communities built around physically demanding, injury-intensive industries.

As a society and as a healthcare system, we have made meaningful strides in treating the addiction that followed. Medication-assisted treatment, behavioral counseling, peer recovery support, and community reentry services have saved countless lives. What remains insufficiently integrated into standard recovery programming, however, is sustained, systematic attention to the chronic pain that initiated the cycle and continues to exert physiological pressure on the recovering individual every day. Pain does not enter remission because sobriety is achieved. In the absence of opioids, a lumbar disc compressed in a mine is still compressed. A rotator cuff torn on a processing line is still torn. The nociceptive signals traveling from these injury sites to the central nervous system do not stop — and in early recovery, without the analgesic buffer of opioids, they may feel more acute, more intrusive, and more neurologically proximate to the drug-seeking pathways forged during years of opioid use.

The CravAlert® system addresses this gap directly. Chronic pain exacerbations produce characteristic physiological signatures — elevated heart rate, increased respiratory rate, reduced HRV reflecting autonomic dysregulation under pain load, altered activity and postural patterns captured by accelerometry, and skin temperature fluctuations reflecting peripheral vascular nociceptive responses — that the deep auto-encoder can distinguish from baseline noise and flag for PRSS intervention. A PRSS who receives a chronic pain alert can immediately contact the participant, validate their experience, deploy non-pharmacological coping strategies such as pain self-management techniques and intervening at the precise moment when the pain-to-craving-to-relapse cascade is most interruptible. The 22 chronic pain alerts in this study represent 22 documented interventions at a point in the relapse pathway that, in any conventional recovery model, would have been invisible.

The iRPM Index as a Unique Digital Phenotype

A conceptually significant contribution of the CravAlert® Intelligent RPM (iRPM) system is its generation of what may be described as a unique digital phenotype for each patient — a dynamic, continuously updated physiological and behavioral signature that represents the individual's characteristic pattern of autonomic regulation, activity rhythms, sleep architecture, and stress reactivity across the recovery continuum. Unlike population-level diagnostic criteria or standardized assessment tools, the iRPM architecture does not compare a patient to an external reference population. It compares each patient to themselves, across time and context, building an individualized physiological portrait with every hour of continuous monitoring.

This digital phenotype is constructed from the convergence of multiple data streams — ECG-derived HRV, heart rate, respiratory rate, skin surface temperature, activity level, posture, and GPS — stratified across the four phase-specific activity-posture windows that define each individual's 24-hour physiological architecture. The resulting baseline is not a fixed threshold but a living model: dynamically adjusted as the patient's physiological patterns evolve through early recovery, stabilization, and longer-term sobriety. The deep auto-encoder learns the compressed representation of this individual's normal state and becomes increasingly sensitive to deviations that are personally meaningful, as opposed to statistically anomalous at the population level.

The clinical implications of the digital phenotype concept are substantial. In conventional medicine, phenotyping refers to the observable characteristics of an organism or patient that emerge from the interaction of genotype and environment. The iRPM digital phenotype is an analogous construct in the behavioral health domain: it captures the measurable, dynamic expression of each patient's neurobiological vulnerability, emotional reactivity, autonomic tone, and environmental stress exposure — precisely the factors that govern relapse risk in OUD recovery. Two patients with identical diagnoses, identical treatment histories, and identical social circumstances may manifest entirely different digital phenotypes — one characterized by daytime anxiety peaks and robust nocturnal HRV recovery, the other by overnight arousal and blunted stress-response variability. The iRPM system recognizes and responds to these differences individually, enabling truly personalized recovery support rather than standardized population-level care.

Furthermore, the digital phenotype evolves over the course of recovery in ways that may serve as objective biomarkers of recovery progress. Improvements in HRV, normalization of diurnal heart rate patterns, reduced frequency and amplitude of anxiety-related physiological deviations, and extension of sleep-phase stability may all be quantifiable indicators of neurobiological recovery — providing a longitudinal physiological record that supplements, and may ultimately inform, clinical treatment decisions. As the CravAlert® dataset grows across larger cohorts and longer follow-up periods, the digital phenotype infrastructure may yield predictive models of sufficient precision to identify, weeks in advance, which patients are approaching physiological decompensation and require proactive intervention intensification. This represents a frontier in precision behavioral medicine that the CravAlert® iRPM system is uniquely positioned to explore.

Mental Health Comorbidity and the Case for Expanded CravAlert® Applications

The finding that 71.8% of all CravAlert® alerts — 442 of 616 total events — were generated by mental health conditions (anxiety and stress: 64.6%; major depression: 7.1%) demands both clinical interpretation and programmatic reflection. This figure is consistent with the extensive epidemiological literature documenting the co-occurrence of substance use disorders and psychiatric conditions, but it takes on particular significance in the context of a continuous physiological monitoring platform: it means that in the day-to-day operational reality of CravAlert®, the system is functioning as a mental health detection and intervention platform as much as — if not more than — a SUD relapse prevention tool.

The comorbidity of SUD and mental health disorders is not a clinical footnote — it is the central epidemiological reality of addiction medicine. Nationally, more than half of individuals with SUD meet criteria for at least one co-occurring psychiatric disorder, and the prevalence rises further in treatment-seeking populations and in communities like those of WV Region 2, where poverty, unemployment, adverse childhood experiences, and community-level trauma compound individual vulnerability [11, 12]. Anxiety disorders and major depressive disorder are the most prevalent co-occurring conditions in OUD populations, and their relationship to relapse is well-characterized: negative

affect, anhedonic states, and anxiety hyperarousal are among the most potent activators of drug-seeking behavior, operating through overlapping limbic and prefrontal neural circuits that opioids — through their euphoriant and anxiolytic properties — directly modulate [9]. For many individuals with OUD, opioids were never merely analgesics; they were self-administered antidepressants and anxiolytics, and the emotional dysregulation that emerges in their absence is among the most clinically challenging aspects of early recovery.

What the CravAlert® alert data demonstrate is that the physiological signatures of anxiety and depression — reduced HRV, elevated heart rate and respiratory rate, altered diurnal autonomic rhythms, and disrupted activity patterns — are detectable continuously, in real time, before the patient has articulated or even consciously recognized their deteriorating mental state. The deep auto-encoder's ability to identify these deviations from the patient's personalized baseline and generate an alert enabling immediate PRSS contact represents precisely the early intervention model that has long been theorized but rarely operationalized in community mental health settings. A PRSS reaching a participant in the early physiological stages of an anxiety escalation or depressive episode — before that escalation has translated into craving, drug-seeking, or behavioral decompensation — is operating at the most clinically impactful point in the relapse cascade.

The implications of this finding extend well beyond the SUD treatment context. The physiological signatures monitored by CravAlert® are not diagnosis-specific: anxiety, depression, and autonomic dysregulation manifest with similar physiological characteristics across generalized anxiety disorder, PTSD, bipolar disorder, schizophrenia spectrum conditions, and other major psychiatric diagnoses. A platform capable of detecting these signatures continuously and triggering trained peer interventions in real time is, in principle, a platform for proactive mental health support across a broad range of psychiatric populations. The 71.8% mental health alert rate in this pilot is therefore a proof-of-concept for the expanded deployment of CravAlert®-class RPM as a standalone mental health monitoring and intervention infrastructure — one that could reduce psychiatric emergency department utilization, prevent inpatient admissions, and provide continuous support to individuals in community mental health settings who are currently monitored only episodically, if at all. Future research should explicitly explore this expanded application, beginning with populations in which physiological early warning signals of psychiatric decompensation carry the highest clinical stakes.

The Deep Auto-Encoder and Machine Learning Infrastructure

The choice of a deep auto-encoder architecture for anomaly detection represents a methodologically sophisticated approach to the clinical problem of relapse prediction. Unlike supervised classification models that require large labeled datasets of confirmed relapse events — which are inherently rare and difficult to capture — the auto-encoder learns normal physiological patterns and detects deviations, making it particularly well-suited to low base-rate clinical events such as confirmed relapse [5]. The training corpus of over 1.2 million tagged data points represents a substantial evidence base for model calibration, enabling the system to differentiate between physiological stress patterns associated with cravings, anxiety, depression, and occupational exertion — the last category being the primary driver of the 6.5% false positive rate observed in this cohort.

The Bimodal Alert Pattern and PRSS Staffing Implications

The identification of a bimodal 24-hour alert distribution — with Peak 1 spanning late afternoon through evening and Peak 2 in the early morning hours — has direct operational implications for PRSS program design. Traditional peer support models relying on business-hours availability are poorly matched to the temporal distribution of physiological vulnerability in this population. The CravAlert® data suggest that PRSS staffing models must include evening and overnight coverage to intercept the substantial proportion of craving and anxiety alerts occurring between approximately 21:00 and 10:30. This finding aligns with clinical observations that late evenings and early mornings are peak vulnerability periods for relapse in OUD recovery.

Nutritional Context and Alert Vulnerability

The finding that the mean time since last meal before an alert was 164.83 minutes (median 125.00 minutes), with a right-skewed distribution extending to 800+ minutes, introduces nutritional dysregulation as a potentially modifiable precursor to craving and anxiety episodes. Blood glucose fluctuations associated with prolonged fasting are known to increase cortisol levels, impair prefrontal executive function, and heighten emotional reactivity — all factors that increase vulnerability to craving and relapse [9]. This finding supports integration of nutritional counseling into comprehensive CravAlert® wraparound services and may warrant dedicated investigation in future studies. The inclusion of last-meal timing as a participant-reported variable at point of alert generation was prompted by the expert insight of Christina Veselak, founder of the Academy for Addiction and Mental Health Nutrition, whose work on the relationship between nutritional status, blood glucose regulation, and craving vulnerability in SUD populations informed this line of inquiry.

User Experience and Engagement

The user experience data — particularly the 91% peer recommendation rate and 80% rating of the program as crucial support — indicate high participant acceptability and perceived value. The 54% Recovery Impact score, while lower than other dimensions, may reflect the inherent difficulty of attributing recovery progress to any single intervention in the complex, multi-factorial context of SUD treatment. The 78% Ease and Comfort score suggests that participants largely adapted well to continuous device wear, though the 3% dermatological adverse event rate underscores the ongoing importance of adhesive formulation optimization.

Data Security and Regulatory Compliance

The CravAlert® platform maintains the highest standards of data security relevant to SUD populations. End-to-end encryption protects all physiological data in transit and at rest. Full HIPAA and 42 CFR Part 2 compliance ensures SUD-specific confidentiality protections. The VeeOne Health® infrastructure holds HITRUST CSF and ISO 27001:2013 certifications, with secure access controls, role-

based authorization, and complete audit tracking. These measures are essential not only for regulatory compliance but for building participant trust in a population with historically justified concerns about data confidentiality.

Limitations

Several limitations merit acknowledgment. First, this pilot study lacks a randomized control group, limiting causal inference. Second, rural broadband infrastructure challenges in WV Region 2 intermittently disrupted real-time data transmission for a subset of participants, introducing gaps in the physiological record and potentially delaying alerts. Third, legal events — arrests and incarceration — caused program discontinuation for several participants, potentially underestimating relapse-proximate physiological patterns. Fourth, self-reported nutritional and behavioral data at alert time may be subject to recall bias. Fifth, the false positive rate of 6.5%, though modest, reflects the ongoing need for occupational context integration into ML threshold calibration.

Conclusions

The CravAlert® system — integrating the VivaLink® VV330 wearable biopatch, a deep auto-encoder machine learning analytics platform trained on over 1.2 million data points, and structured just-in-time PRSS interventions — demonstrates compelling preliminary efficacy as a technology-augmented, human-centered approach to SUD relapse prevention in rural West Virginia. In a 100-participant cohort, the program generated 616 clinically actionable alerts across seven categories, enabling real-time peer interventions that appear to be associated with a relapse rate of 2–5% at 3–6 months against a national baseline of 60–85%, arrest rates of 4–5% vs. 30–49% nationally, and MAT retention of 69–74.5% vs. 29–46.2% nationally.

Two contributions of particular significance emerge from this study beyond the headline outcome data. First, the detection of 22 chronic pain exacerbation alerts illuminates a dimension of relapse risk that conventional recovery programs systematically overlook: the persistent nociceptive burden carried by individuals whose addiction originated in occupational injury — the coal miners, loggers, and poultry plant workers of Appalachia. Recognizing chronic pain as a continuous relapse signal, and equipping PRSS staff to respond to it in real time, represents a fundamental expansion of what recovery support can and should encompass. Second, the iRPM system's construction of a unique digital phenotype for each patient — a continuously updated, personalized physiological signature reflecting that individual's specific autonomic profile, stress reactivity, and recovery trajectory — positions CravAlert® at the frontier of precision behavioral medicine. This is not population-level care applied to individuals; it is genuinely individualized monitoring and response, calibrated to each person's neurobiological reality. Third, the finding that 71.8% of all alerts were generated by mental health conditions — primarily anxiety, stress, and depression — confirms that the CravAlert® platform is functioning as a co-occurring disorder management system and establishes proof-of-concept for its expanded application to primary psychiatric populations beyond the SUD context.

Priority next steps include: (1) a randomized controlled trial to establish causal attribution of outcomes; (2) integration of Medicaid RPM billing pathways (CPT 99453–99458) for program sustainability; (3) extended PRSS coverage hours informed by the bimodal alert distribution; (4) integration of dedicated chronic pain management services for participants with occupational injury histories; (5) longitudinal study of digital phenotype evolution as a biomarker of recovery progress; (6) prospective investigation of CravAlert® deployment in primary psychiatric populations — including anxiety disorders, PTSD, and major depressive disorder — to evaluate its utility as a standalone mental health monitoring and intervention platform; and (7) rural broadband infrastructure investment to ensure consistent monitoring continuity across WV Region 2's geographically dispersed population.

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Conflict of Interest

R.M. serves as Research Professor at Future Generations University and Program Director at Potomac Highlands Guild, Inc., and is a co-developer of the CravAlert® program. S.S., A.K. (Khokhar), A.R.K., and M.S. are employed by VeeOne Health®, which provides the RPM analytics infrastructure for CravAlert®. H.P., M.P., B.M., E.S., and J.B. declare no conflicts of interest. J.B. contributed data visualization for this manuscript. All authors confirm this disclosure does not affect the integrity of the research or its reported findings.

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