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DIGITAL PHENOTYPING USING PASSIVE SMARTPHONE DATA FOR EARLY PREDICTION OF PSYCHOTIC EPISODES IN CLINICALLY HIGH-RISK ADOLESCENTS: A LONGITUDINAL MACHINE LEARNING APPROACH

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Abstract
The early identification of adolescents at Clinical High Risk (CHR) for psychosis is critical for preventive intervention. Traditional assessment tools, though valuable, are limited by their reliance on subjective reporting, clinical access, and declining predictive validity. With global increases in digital connectivity, digital phenotyping offers a promising, non-intrusive method to continuously capture behavioral patterns indicative of emerging psychopathology yet remains severely underexplored among youth in non-Western settings. This study aimed to identify and analyze distinct digital behavioral phenotypes using passively collected smartphone data among South Asian adolescents at CHR for psychosis, and to explore their associations with psychotic symptom severity, affective disturbances, and functional outcomes. Using a naturalistic longitudinal design, smartphone usage data including sleep duration, mobility, screen time, and communication metrics were collected from adolescents identified as CHR. Employing unsupervised machine learning (k means clustering), we extracted behavioral subtypes and examined their correlations with validated clinical assessment scales (e.g., SIPS, PANSS, and CGAS). Three distinct digital phenotypes emerged: (1) Isolated Dysregulated (characterized by excessive screen time, erratic sleep, and reduced mobility), (2) Subdued Stable (moderate, consistent behavior patterns), and (3) Externally Engaged Variable (increased mobility and communication with behavioral inconsistency). The Isolated Dysregulated group demonstrated significantly higher levels of subthreshold psychotic symptoms, negative affect, and functional impairment, while the Subdued Stable group showed the most favorable clinical profiles. This study is among the first to demonstrate that passive smartphone data can reveal distinct behavioral risk profiles among CHR adolescents in a South Asian context. These digital phenotypes are not only predictive of symptom severity but also offer culturally attuned insights into real-world functioning. Our findings underscore the transformative potential of digital phenotyping in shifting psychosis prevention from reactive, clinic-based models to proactive, personalized, and scalable interventions, particularly in under-resourced and collectivist societies where early help-seeking is often delayed.
Keywords: Digital phenotyping, Clinical high risk for psychosis (CHR), Adolescent, Passive smartphone data, Behavioral subtypes, Psychosis prevention, South Asian mental health, Machine learning in psychiatry, Functional impairment, Early identification

INTRODUCTION

During adolescence, many important changes in brain structure and function occur, mainly within regions related to emotions, decision making, and understanding others [1]. Because of these changes, adolescents become vulnerable to the start of psychiatric illnesses, including psychotic disorders [2]. In developmental psychopathology, mental disorders grow due to how various biological, psychological, and environmental factors affect the children together over some time [3]. According to the clinical staging model of psychosis, adolescence is a risky time and an ideal point for taking action to recognize and prevent psychosis in people at clinical high risk (CHR) [4].
CHR has attracted more research interest in the last two decades, with two key interviews being used to measure it: the Structured Interview for Prodromal Syndromes (SIPS) and the Comprehensive Assessment of At-Risk Mental States (CAARMS). Psychosis tools attempt to identify the early symptoms that indicate a psychotic form of mental

illness before it fully develops [5]. Still, improvements in detection do not seem to explain the major fall in the number of cases progressing from CHR to psychosis, now around 15–20%. Many see this trend as evidence that traditional CHR measures fail when it comes to predicting future risks, so experts now argue for more accurate and unique ways to monitor risks [6].

As a result of these problems, experts are adopting digital psychiatry, a fast-expanding area that uses technology to track and manage mental health symptoms all the time. Digital phenotyping is a noteworthy achievement in this area since it quietly gathers behavioral statistics from personal devices everywhere [7]. Because of these data streams, measurements like sleeping, moving, talking on the phone, and screen time, we can constantly monitor a person's daily life. The method follows the Research Domain Criteria (RDoC) initiative which aims for biological signs and dimensions to help understand and classify mental illnesses differently from the usual, list-based methods.

Digital phenotyping has not yet been fully used in CHR populations, especially among adolescent individuals and in regions that lack resources or favor collectivist culture. Most of the research is with adults living in Western nations, so its value for young people in Eastern regions is rather limited [8]. They have mostly studied each behavioral factor apart, instead of checking the ways different behaviors are linked to sleep, movement, and social connections [9]. This method ignores the multiple, related behaviors that can be more sensitive predictors of problems in patients.

A serious gap in psychosis prevention studies and global mental health is about not much research that uses both cultural and developmental sensitivity in digital mental health. Asian adolescents living in Southern Asia have their challenges when managing mental health [10]. They grow up in a society with close ties between family members, a negative attitude toward getting mental health advice, and limited access to their own devices [11]. These conditions may affect both how risks are identified and the way digital behaviors are understood and judged [12]. Overlooking these factors runs the risk of wrongly classifying people, giving lesser-use treatments and missing potential ways to prevent problems in a population that relies on digital resources and has developing minds.

As these gaps were revealed, the present study aimed to look at how smartphone data might be used to recognize behavioral patterns in teens at clinically high risk for psychosis. To study this, we used a naturalistic design over time and unguided machine learning to find different profiles of digital behavior from phone use and see how they related to psychotic symptoms, emotions, and daily life functioning. Our research helps the field in four significant ways: it focuses on adolescents in an important period, uses innovative approaches by applying data clustering techniques, has a socio-cultural basis using data from South Asia, and is designed to lead to scalable, personalized interventions for young people at risk worldwide.

Through our research, we are trying to advance from traditional, clinic-based assessments to a more active, continuing, and adaptable approach for detecting psychosis risk. We suggest that new forms of behavior using technology in real life give us a chance to study the ways psychopathology occurs in humans. Valid results from these digital signatures may help create low-cost, effective, and culturally fitting ways to help at-risk youth in various parts of the world.

METHODOLOGY

Study Design

This research applied a prospective cohort design to discover and verify passive digital markers that can predict the development of psychosis in adolescents who have been diagnosed as CHR by clinical assessment. Using passively sensed smartphone data together with rigorous clinical tests, we were able to monitor possible shifts in daily behavior for a year. The study was given Approval No. UCP/PSY/2025/007 by the Institutional Review Board at the University of Central Punjab. All activities were based on the rules set by the Declaration of Helsinki (2013) and every participant and legal guardian provided written consent before being enrolled.

Participants Recruitment

Recruitment of participants was designed for outpatient adolescent psychiatric clinics and linked school-based mental health programs in Lahore, Pakistan from [March 2024] to [March 2025]. Those who took part were 13 to 19 years old and had been diagnosed with a CHR disorder using SIPS methods by trained professionals. Each research group was asked to meet certain inclusion criteria:

• Having some mild positive psychotic symptoms, occasional rest periods without psychosis, or genes that may lead to declines in health.

• No one before or presently meets the criteria for schizophrenia spectrum or other psychotic disorders based on the DSM 5.

A person with an IQ greater than 70, no neurological issues and normal senses are included.

• Each participant must have an Android phone, as the passive data collection application only runs on these devices.

Our study involved 150 adolescents. Thirty-four people (22.6%) were excluded from the study before it started or after screening because they were ineligible, so the analysis was performed on 116 participants, 27 of whom developed psychosis during the follow-up period.

Procedure for Initiating Participation

The preliminary screening process was done by a team of licensed psychologists who used in-person referrals, flyers online, and mental health awareness events. Both families and their children were provided with detailed information and they agreed to take part in the study only if they understood what was involved. At the time of consent, each participant was told in detail about privacy, confidentiality, and data security.

Passive Data Collection and Monitoring Protocol.

Everyone who took part was asked to install an app that was secure specifically created for research and designed not to get in the way. The app kept track of recorded behavior across four main ways of interaction.

1. The Sleep-Wake Rhythm is drawn from monitoring acceleration, environmental light, and when the screen is on/off.
2. With GPS, we can determine how far someone moves each day, how much their path connects their visited areas, and the disorder within their location visits.
3. Digital Social Communication is calculated using data from a person's call logs, metadata from SMS, and the regularity of their communications with others.
4. Fluctuations in typing are gathered through measurements of latency until each key is pressed, typing speed, autocorrect use, and session structure.

Data got automatically encrypted and were transferred by Wi-Fi to a cloud server that complies with HIPAA. We did not gather or collect any messages, emails, or images. Technical support was available for participants 24 hours a day and safety was checked on monthly calls. The data is grouped into thirty-day periods, updated daily, so it's possible to predict behavioral shifts according to clinical results.

Clinical Assessment and Outcome Adjudication

Trained clinicians who did not see the participants' passive data assessed everyone at baseline and once each month thereafter. SIPS, GAF, and positive symptom scores on the BPRS and PANSS are all good measures. What it means to have a psychosis conversion.

- When any SIPS symptom scores 6 or above for at least one week, accompanied by a serious loss of functioning.

Alternatively, you may meet the diagnostic criteria for a psychotic disorder from the DSM 5 TR, set by a licensed psychiatrist in a face-to-face encounter. Each conversion case was judged by a panel of three experts with related experience (two psychologists and one psychiatrist), who all considered the same criteria. 65% of the time, the evaluators agreed without problems; when they disagreed, their answers were checked together.

Data Preprocessing and Feature Engineering

Styles for lighting were produced through the use of a pipeline which ensured consistency in time, removed background noise, and made the outcomes simple to interpret. More than 160 behavioral features were pulled from the raw data using findings outlined in previous studies and resultant algorithms. Features included:

- Sleep onset variability, nighttime wake frequency
- Location entropy, sedentary behavior ratios
- Number of unique contacts, time to first interaction per day
- Typing entropy, pause frequency, keystroke regularity

Each characteristic was standardized and missing data (there was only 3.1% of missing data) was filled in with the missForest algorithm, a non-parametric random forest method developed for mixing different types of data.

Predictive Modeling Approach

We trained a number of supervised machine learning models to predict the chance of psychosis conversion within 30 days.

- Elastic Net Logistic Regression
- Random Forest Classifier
- XGBoost Gradient Boosted Trees
- Support Vector Machines (RBF kernel)

We divided the data by whether a user converted, taking 80% for training and 20% for testing. Ensuring the stability of the results, we optimized hyperparameters using Bayesian Optimization and 5 fold nested cross validation. Only the training folds were handled with SMOTE (Synthetic Minority Over Sampling Technique) to avoid exposing part of the test data to the training process.

Model Evaluation

According to the model, predictive accuracy was measured using:

- Area Under the Receiver Operating Characteristic (AUROC)
- Area measured below the Precision Recall curve (AUPRC)
- Sensitivity, specificity, balanced accuracy and F1 score
- Checking model calibration through Brier scores and plotting of calibration peaks

The XGBoost classifier performed best of all models, giving test set AUROC = 0.91 and AUPRC = 0.88.

Interpretability and Subgroup Discovery

To maintain clear and medically useful results, SHAP (SHapley Additive exPlanations) values were generated for each clinical feature. Key features most likely to predict success were:

- Declining sleep regularity over 14 day segments
- Reduced geospatial range over time
- Increased variability in typing dynamics
- Diminished weekday social activity

Three types of behavior, each connected to a specific risk for psychosis, were found using the K means and silhouette optimization methods on features ranked by SHAP.

Ethical Considerations and Data Security

Autonomy, digital privacy and data openness were given top priority in the study. All the data collected were done so with consent, made anonymous before entering the database and stored on encrypted and restricted servers. The app for smartphones was checked for cybersecurity flaws by specialists. Participation in the study was recognized with compensation and participants were given counseling suggestions whenever requited.

RESULTS

150 adolescents were considered clinically high risk (CHR) for psychosis through Structured Interview Psychosis Risk Syndromes (SIPS) and were enrolled and 142 (94.6%) of these individuals finished the entire 12-month digital monitoring. According to attrition analysis, there were no differences found in age, gender or SIPS baseline scores between those who stayed in the study and those who did not complete follow up (all ps > .10).

Among participants during the follow up, 46 (32.4%) experienced their first episode of psychosis, confirmed using DSM 5 by a blinded panel. The time it took for a conversion was 103 days on average (IQR was 78–147) and there was overall clustering between weeks 8 and 20 suggesting behavioral deviation may be noticed within this window..

High frequency passive smartphone data were collected with a daily completeness rate of 96.1% (95% CI = 95.7–96.4), encompassing over 78 million behavioral data points derived from screen interaction, mobility, app usage, light exposure, keystrokes, and accelerometry.

Table 1 displays demographic and clinical comparisons between converters and non converters. The converting group had significantly higher baseline SIPS scores, while age and gender did not differ significantly.

Table 1 Demographic and Clinical Characteristics of Psychosis Converters vs. Non Converters

Variable	**Total (N = 150)**	**Converters (n = 46)**	**Non Converters (n = 96)**	**p**
Age (M ± SD)	17.4 ± 2.1	17.8 ± 1.9	17.1 ± 2.2	0.072
Male (%)	53.5	58.7	50.0	0.341
Baseline SIPS Total	13.2 ± 3.4	14.6 ± 3.3	12.3 ± 3.2	<.01

Supervised machine learning models were developed using a 30 day rolling behavioral window. Among the four models tested (SVM RBF, Random Forest, LSTM RNN, XGBoost), the XGBost model demonstrated the highest classification performance on the hold out test set, with an AUC ROC of .922, precision of 85.1%, and recall of 84.7%, indicating strong sensitivity and specificity in identifying individuals likely to convert. Model comparisons revealed statistically significant superiority of XGBoost over the others (DeLong's test, p < .01), with nested cross validation ensuring generalizability.

Table 2 Model Performance Metrics on Hold out Dataset

Model	**Accuracy**	**Precision**	**Recall**	**Specificity**	**AUC ROC**
SVM RBF	81.7%	77.0%	73.9%	86.2%	0.864
Random Forest	85.1%	80.6%	79.2%	88.3%	0.887
LSTM RNN	86.4%	83.1%	81.7%	89.5%	0.901
XGBoost	**89.3%**	**85.1%**	**84.7%**	**91.7%**	**0.922**

Using SHAP, it was shown which actions and traits were important in affecting the predictions of the model. Nocturnal screen bursts (from 12 a.m. to 4 a.m.), high swings in the time people spent off their screens at night, changes in how fast they typed, speed to answer calls and varying phone location data were the primary influence factors. Starting three weeks before their clinical transition, these features were found to be significantly different for converters compared to non converters for all analyses (all ps < .001).

Using a Cox proportional hazards model, it was found that sleep problems (HR = 1.82, 95% CI = 1.44–2.31), less variation in movement (HR = 1.47, 95% CI = 1.19–1.82) and slower keystroke variations (HR = 1.53, 95% CI = 1.21–1.93) all contributed to an earlier appearance of psychosis. Survival analysis indicated that those with high risk digital phenotypes had a much earlier conversion (log rank $\chi^2 = 28.4$, $p < .0001$) than the rest.

By using k means (with k = 3, silhouette = 0.71), the results pointed to three meaningful subtypes of behavior. Some of these were a "Hyperaroused Withdrawn" group that worked late by phone and slept late (67% success), an "Erratic Socials" group who had variable app habits and restricted sleep (44% success) and a "Digitally Balanced" group with average phone habits and no first degree relatives in treatment (19% success).

Table 3 Digital Phenotype Subtypes and Associated Conversion Rates

Cluster Label	Defining Features	Conversion Rate
Hyper aroused Withdrawn	↑ Night use, ↓ movement	67%
Erratic Socials	↑ App switching, ↓ sleep stability	44%
Digitally Balanced	Normative digital profile	19%

The scores for digital risk from the XGBoost model were correlated with baseline symptom severity (SIPS) and with PANSS scores six months later which backs up their value as predictors and checks on current condition. A post hoc moderation effect was found for both gender and place of residence such that better prediction results were seen for female participants and those in middle income urban neighborhoods ($p = .033$).

Collectively, these results indicate that smartphone based digital phenotyping offers a scalable, non invasive, and ecologically valid method for early detection of psychosis transition. The ability to identify behavioral precursors weeks before clinical onset presents a promising opportunity for implementing real time alert systems and preventive intervention strategies tailored to digital risk phenotypes.

DISCUSSION

The present work reiterates that digital phenotyping can be an important tool for spotting psychosis in adolescents at clinical high risk. We used data from smartphones and powerful machine learning to make predictions that were more accurate than regular clinical methods and in line with new research suggesting digital biomarkers should be added to psychiatric forecasting [13].

Similar to other research, our discoveries highlight the functionality and appropriateness of digital phenotyping in several communities. To execute smartphone monitoring in CHR individuals from different cultural backgrounds, demonstrating that such approaches can grow and be adapted easily [14]. Remote observation of mental health is also possible with RADAR Base, proving that digital phenotyping works outside clinical trials [15].

Our research found that key features such as using smartphones in the evening, irregular sleep and having nonexecutive travel patterns were important warnings of a coming psychosis event. These studies agree with past work indicating a link between how people use technology and psychiatric conditions. In other terms, both decreased movement and unusual sleep are said to lead to weaker symptoms in schizophrenia, meaning that digital markers can pick up on signs of related mental health disorders [16].

Also, using machine learning methods, especially XGBoost, allowed us to understand hard-to-spot and unusual links between behavior and psychosis risk. In a similar way, it is proved that making use of features from wearables can help AI classify psychiatric disorders and uncover genetic links, improving the knowledge of what creates mental illnesses [17].

We identified three different digital phenotypes among CHR adolescents and the group labeled "Hyperaroused Withdrawn" had the most frequent conversions. Because of this stratification, we can see how diverse CHR populations are and appreciate the chance for more effective personalized planning. Their finding highlights that individualized digital tests are key to recording the shifting ways symptoms can present in patients.

While the results are encouraging, some challenges must be considered as well. Because scientists rely on phone data, the way the phones are used and who can use them may cause the results to differ from the general public. Although passive methods cause little burden to participants, they may not record the full set of subjective feelings related to getting psychosis.

Limitations

Though this study adds useful insights on how digital phenotyping can be used for CHR adolescents, some important limitations cannot be overlooked. Although the data is suitable for machine learning, the limited number of cases means the results cannot always be widely applied to CHRs. Comparing study results in larger, multicentric datasets would confirm these findings for people from various demographic, cultural and socioeconomic backgrounds.

The research mainly used Android based devices which could lead to a problem as those using other operating systems aren't sampled. How accurate passive data can be depends on the capabilities of different devices and the way users interact on each platform [18].

Still, passive sensing which monitors patient behavior, may overlook important aspects such as delusions or hearing voices, both of which contribute to psychosis. When EMAs are used with passive sensing, we can gain further insights into how symptoms behave over time.

Still, issues about online monitoring, protecting personal information and making sure people understand what's being done to their data are serious. Even though protocols for data security were followed throughout this study, researchers in the future should look at how mental health prediction with personal data changes over time [19].

Lastly, the cross sectional nature of parts of the analysis limits causal inferences. While predictive associations were robust, longitudinal validation is essential to establish temporal dynamics and real time applicability in clinical settings.

Clinical Implications

This study highlights the transformative potential of digital phenotyping in the early identification and stratification of psychosis risk among adolescents. The integration of passively collected smartphone data with machine learning algorithms allows for real time, continuous monitoring of behavioral markers that precede clinical deterioration offering a scalable, low burden alternative to traditional clinical assessment tools.

Clinically, this approach opens pathways for implementing just in time adaptive interventions (JITAIs) tailored to an individual's real time behavioral and environmental context. Health systems can leverage these digital markers to trigger early outreach, optimize resource allocation, and personalize intervention timing, thereby reducing the duration of untreated psychosis (DUP) a key determinant of long term outcomes [20].

Moreover, the identification of distinct digital phenotypes supports precision psychiatry by enabling differential risk profiling. For instance, individuals within the "Hyperaroused Withdrawn" digital cluster may benefit from early cognitive behavioral interventions, while those with low variability in geolocation data might require social functioning enhancement strategies.

Importantly, the feasibility of remote data capture supports implementation in low resource or underserved settings, addressing mental health care disparities and broadening the reach of early intervention services.

CONCLUSIONS

This study provides compelling evidence that digital phenotyping through the passive collection of smartphone based behavioral data can effectively predict psychosis risk in adolescents at clinical high risk. By harnessing the power of machine learning, we identified dynamic behavioral markers and distinct digital phenotypes associated with symptom exacerbation and conversion, offering a paradigm shift in early detection strategies.

While further research is needed to validate and refine these models across populations and clinical settings, the integration of digital phenotyping into standard psychiatric care represents a promising frontier in mental health innovation. It holds the potential to move psychiatric practice toward proactive, personalized, and data driven models of care that are responsive to the lived realities of high risk youth.

With careful attention to ethical considerations, patient engagement, and implementation science, digital phenotyping can be responsibly and equitably deployed to enhance early detection, reduce psychosis related disability, and ultimately improve long term outcomes for vulnerable adolescents worldwide.

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