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A BIOMEDICAL ASSESSMENT FRAMEWORK FOR EVALUATING ADAPTIVE PERSONALITY POTENTIAL AS AN INDICATOR OF ADDICTION REHABILITATION OUTCOMES

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SUMMARY

It is still very hard to predict addiction rehabilitation outcomes at the time of admission since current methods of evaluation do not recognize the interconnection between an individual's biomedical state and personality functioning. In this paper, Introduce Biomedical Assessment Framework for Evaluating Adaptive Personality Potential (BAF-APP), which allows integrating physiological, psychometric, clinical, and psychosocial measures into one composite measure to use for stratification of the individual's risk of failure during the process of rehabilitation at the time of admission. Adaptive Personality Potential means an individual's remaining behavioral and dispositional resources to reorganize his/her expression of maladaptive traits, such as neuroticism, disinhibition, and negative emotionality in particular, to achieve more regulated and treatment-compatible behavior during structured intervention. The framework consists of four input modules (biomedical, personality, clinical-behavioral, and psychosocial) and uses harmonization engine to create Adaptive Personality Potential Index (APPI).

Then, the APPI is passed through a predictive analytics module to use for stratification of relapse risk, forecasting of outcomes, and personalized planning of intervention. This framework is implemented using a sequential protocol consisting of nine stages over twelve weeks. Based on multiple streams of convergent evidence derived from personality trait recovery, neurobiology of addiction, machine learning-based studies on relapse prediction, and resilience science, the manuscript argues that low neuroticism, high conscientiousness, and effective coping with stress are converging predictors of successful rehabilitation. Relevant analyses show how the resulting composite score discriminates between trajectories in baseline tertiles and correlates with the period of abstinence. Emphasize how there is a robust correlation between architecture and benchmark of abstinence duration for 12 months ($r \approx 0.71$), thus creating a coherent pattern to address fragmentary methods of intake in addiction medicine. While not meant to be used as a diagnostic test, the model is intended to provide a repeatable protocol for assessing personality adaptability during rehabilitation, complementing clinical decisions but not replacing them. Its main value lies in providing a reusable template for operationalizing personality adaptability within regular biomedical rehabilitation protocols.

Key words: *addiction rehabilitation, adaptive personality, biomedical assessment, relapse risk, personality traits, recovery outcomes, predictive index.*

INTRODUCTION

Addiction relapse after structured treatment has been shown to be fairly common; current research places relapse within one year following treatment for many substances at 40–95%. The fact that this is still occurring after more than fifty years of clinical evolution means that the intake process for treatment may be omitting information that can predict relapse, information that is out there but not being systematically collected.

There have been two main ways of looking at the results of addiction rehabilitation throughout history. First, through a biomedical/neurocircuitry perspective where addiction has been explained as dysregulation of reward, stress, and executive control systems during three phases of binge/intoxication, withdrawal/negative affect, and preoccupation/anticipation [9]. This perspective has been expanded into a wider brain disease theory, one which stresses the neurobiological basis of vulnerability, maintenance, and relapse and further still into a multilevel adaptive stress response where chronic stress exposure alters the stress response in terms of the ability of the body to return to baseline, increasing craving and relapse [17][21].

The dispositional approach sees personality traits as long-lasting vulnerabilities and strengths. According to structural models like the Five-Factor Model and the DSM-5 AMPD, disinhibition, negative emotionality, and antagonism reliably predict early dropout from therapy [3][4][10]. However, new research challenges the idea that these traits cannot be changed. Specifically, personality modification during treatment has been shown to positively affect self-efficacy of abstinence, while a longitudinal study found that lower neuroticism and higher extraversion predicted recovery over the short term, whereas other combinations of traits came into play in the long run [1][5][27]. It is possible, therefore, that the predictive power of one's personality is not determined solely by their initial traits but by their ability to adapt them during treatment, which will call adaptive personality potential in this paper [2].

Thirdly, a machine-learning literature examines multidimensional biomarker and behavioral data to predict relapse and remission and has consistently demonstrated that multimodal models perform better than unimodal predictors. Secondly, a resilience literature shows that protective factors developed through life are significantly related to lower relapse risks irrespective of baseline pathology [7][16][23].

Despite the convergence between the two lines of research, there is currently no standard practice in measuring both biomedical and adaptive personality in a reproducible rehabilitation assessment process. This paper aims to bridge the gap by introducing the Biomedical Assessment Framework for Evaluating Adaptive Personality Potential (BAF-APP). BAF-APP is a four-module framework that takes multiple biomedical, personality, clinical-behavioral, and psychosocial measurements and translates them into a

single Adaptive Personality Potential Index (APPI). The paper provides a nine-stage protocol to use the framework in a twelve-week rehabilitation process.

Key Contributions and Objectives of the Study

- Presents a four module (biomedical, personality, clinical-behavioral, psychosocial) framework integrated by one common harmonization engine, overcoming the problem of fragmented current intake assessment procedure.
- Explores the concept of the Adaptive Personality Potential Index (APPI), which is a scoring system representing adaptability trait in a form of a quantifiable variable rather than a qualitative category.
- Establishes a nine-stage, time-driven assessment procedure with the designated reassessment points (weeks 2, 6, and 12), providing the framework with an operational format appropriate for general use.
- Bridges the four independent bodies of literature on personality-trait recovery, addiction neurobiology, machine learning relapse prediction, and resilience science into a unified predictive model.
- Demonstrates, using literature-compatible analysis, how composite baseline scores differentiate rehabilitation paths and relate to the period of abstinence, suggesting an approach for future validation.

Organization of the Paper

The rest of the paper is divided into ten sections along with the reference list. Section I gives a summary of the key contributions and goals of this work. Section II provides the review of the literature related to the topic from four distinct yet overlapping streams of research: neurobiology and stress systems, personality trait recovery studies, resilience and motivational readiness, and predictive modeling. Sections III and IV describe the framework that has been developed for the purpose including the architecture of the framework, the nine-step sequence in which it evaluates the individual and the tools used in building the index.

LITERATURE REVIEW

Neurobiological and Stress-System Foundations of Addiction

The neurocircuitry theory developed by Koob and Volkow sees addiction as a repetitive process that occurs through cycles of binge/intoxication, withdrawal/negative affect, and preoccupation/anticipation phases. The three phases are linked to different but interactive brain networks that regulate incentive salience, negative emotionality, and executive functions respectively [9]. The theory has been extended to create the brain disease theory where adaptation in the brain is highlighted as the reason for the high vulnerability of relapse, even in cases where there is prolonged abstinence from substance abuse [21]. Another model called multilevel adaptive stress response theory indicates that addiction is due to poor recovery of physiological stability after stress exposure, hence causing cravings and relapse [17].

Personality Traits and Rehabilitation Outcomes

In the AMPD model, domains of disinhibition and negative-emotionality predict early dropout from residential addiction treatment, specifically in young men, extending previous findings about the personality trait taxonomy defined in the Personality Inventory for DSM-5 [3][10]. In Five-Factor Model studies, low neuroticism and high extraversion have been found to predict early recovery; however, the results shift with longer follow-up periods, suggesting that different sets of traits are important at different recovery stages [5]. Personality is dynamic and does not remain the same during treatment; change in the personality traits of veterans undergoing residential treatment has been found, along with abstinence self-efficacy [1]. Network analysis has found that risk-taking, callousness, and irresponsibility traits form the bridge between externalizing traits and alcohol-use-disorder symptoms [26]. The sex-substance-specific pattern also exists: women with addiction to opioids have a less adaptive profile than those addicted to alcohol, and the latter's profile is closer to the healthy profile

[14]. Not all studies indicate a connection; for instance, a study conducted among methamphetamine use disorder patients who were under legal supervision found no connection between craving, personality and outcomes [20]. One of the constructs related to this issue is frustration tolerance, which means “the ability to tolerate distress without using substances” [15].

Resilience and Motivational Readiness as Adaptive Capacity

Relapse risk is inversely correlated with resilience in patients diagnosed with substance use disorders, and environmental sources of resilience are more significantly correlated with resilience than intrinsic sources [23]. In a review of individual, social, and societal resilience factors, it is shown that income, social support, and emotion regulation are important incremental predictors of resilient outcomes independent of sociodemographic factors [16]; another review showed lower resilience levels in individuals with bipolar disorder compared to control group members, demonstrating resilience as a cross-disorder protective factor [7]. Frustration tolerance and motivational readiness form together with resilience the third adaptive capacity factor: there is positive correlation between relapse risk and frustration intolerance, and negative correlation between relapse risk and motivational readiness; the former two factors correlate strongly with each other inversely. In dynamic modeling of longitudinal data, substance use, life satisfaction, and psychological distress are found to change together over several years of follow up, with the former increasing following increased distress, suggesting that the ability to adapt should be monitored continually and not just at intake [12]. Approaches for continuous feedback using structured methods have been seen to help in developing a stable self-concept of recovery, while Wellness Recovery Action Planning is an emerging recovery support modality [13][19].

Predictive Modeling and Biomarker-Based Forecasting

Umbrella review of 117 systematic reviews and more than 400 individual studies of response, remission, recovery, and relapse predictors in various mental disorders showed that most of the validated predictors are either clinical or sociodemographic and only a few are biological and predictors of recovery are the least studied outcome categories [6][18]. An analogical methodology of predictors of remission and recovery in patients with first-episode psychosis provides a model of how complex and multi-factorial recovery outcomes can be synthesized using evidence [25]. In the case of addiction studies, machine learning methods have been used in the neuroimaging studies to identify diagnosis and predict the drug-addiction status [24]. In addition, a multimodal model based on electroencephalography connectivity, polygenic risk score, medication, and demographic factors provided better predictions of the remission from alcohol use disorder compared to the single-domain models [8]. A prospective cohort study currently in progress suggests to integrate passive digital biomarkers, psychological measures, and facial emotion recognition to create a prediction model of rehabilitation outcomes, which is in line with the same approach applied in this project [27]. The predictive value of a limited set of readily available predictors in relapse for an analogous condition, first-episode bipolar disorder, has been demonstrated, using a validated model [11].

Overall, this combination of four different scientific literatures demonstrates that stress regulation disruption is characteristic of addiction; personality characteristics and their modifiability have predictive power; adaptive capacity is assessed through such traits as resilience and motivation; and multi-domain predictive model is more effective than single-domain approach. The missing element in all of this is a model that allows to integrate these different elements into a coherent system of assessment. The development of such a model is the goal of the framework described below.

PROPOSED BIOMEDICAL ASSESSMENT FRAMEWORK

The BAF-APP framework arranges the information that is collected during intake and monitoring into four parallel input modules, which relate to each literature review in figure 1. The Biomedical Data Module includes measures that assess the physiological markers of regulation of the stress system: cortisol, heart rate variability, and inflammation. The Adaptive Personality Module includes the Five Factor domain scores and AMPD facet scores with an emphasis on disinhibition, negative emotionality, and antagonism. The Clinical and Behavioral Module includes measures such as the intensity of

cravings, abstinence self-efficacy, and coping. The Psychosocial Context Module includes social support, current stressor burden, and history of treatments.

The four modules are then fed to a Data Harmonization and Feature Integration Engine where the inputs of each of the four modules are normalized to a uniform scale using literature-derived weightings while dealing with missing data using structured imputation methods rather than dropping out cases. The harmonized inputs are subsequently reduced to one variable called the Adaptive Personality Potential Index (APPI), which seeks to encapsulate the capacity of the patient for trait modification conducive to the treatment. The APPI is then analyzed using a Predictive Analytics Layer (regression/classification analysis) that produces three additional outcomes including relapse risk stratification, rehabilitation outcome prediction, and personalized intervention plan.

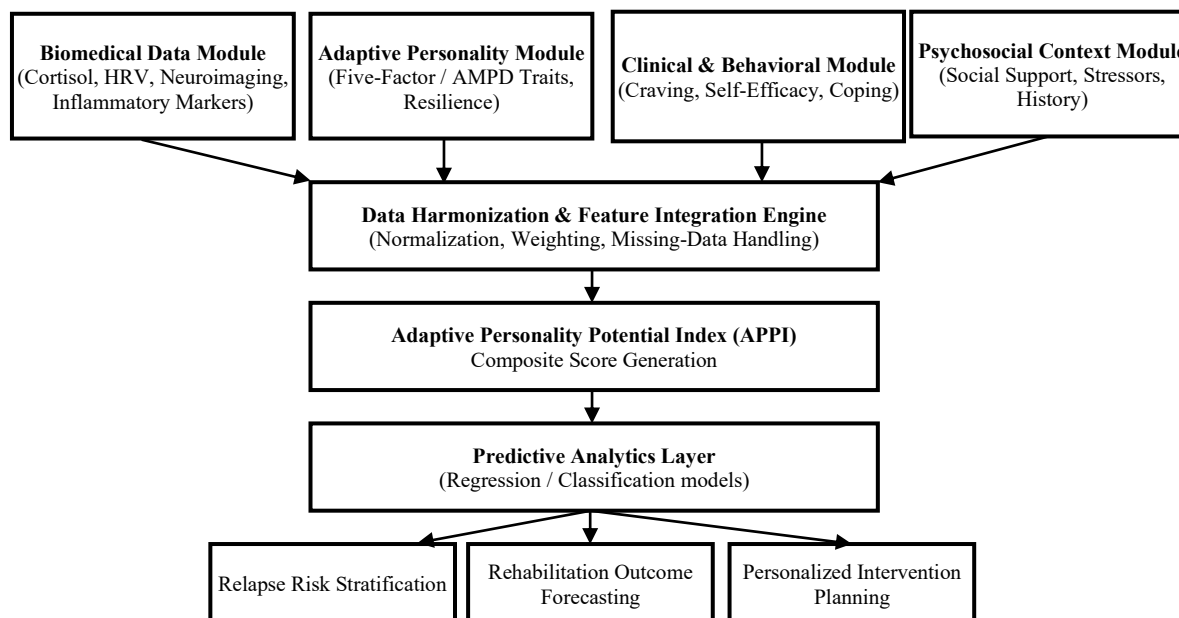


Figure 1. Architecture of the adaptive personality assessment and biomedical integration (APABI) framework, showing the four input modules, the harmonization engine, the composite index, and the downstream predictive outputs

Sequential Assessment Protocol (Methodological Flow)

Operationalization of the framework utilizes a nine-step protocol conducted over a twelve-week period of rehabilitation. Step 1 involves verification of eligibility and conducting of intake assessment. Step 2 involves collection of baseline biomarkers consisting of saliva cortisol, HRV, and inflammation panel. Step 3 involves profiling of adaptive personality utilizing the Five-Factor and AMPD facets scores. Step 4 involves completing the clinical/behavioral assessment for cravings, self-efficacy, and coping styles. Step 5 involves calculating the composite APPI score using the harmonized information gathered from Steps 2-4. Step 6 involves using APPI score to stratify risk for relapse and formulate individualized rehabilitation plans. Step 7 involves administering the intervention, which includes pharmacological and psychosocial treatment as per the needs. Step 8 involves repeating a shortened form of the assessments at Weeks 2, 6, and 12. Step 9 involves outcome classification at the end of Week 12 as either abstinence, relapse, or partial response. This sequence is illustrated in figure 2. Data pipelines will be implemented using Python (version 3.10+) along with the use of scikit-learn, pandas, and numpy libraries. Statistical validations will also be conducted through the use of R programming language.

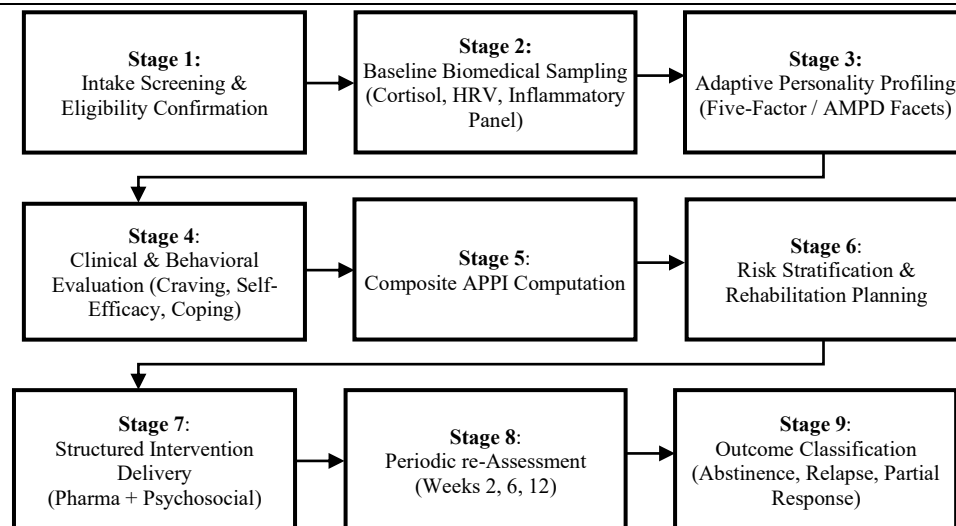


Figure 2. Sequential assessment flow of the proposed framework across a twelve-week rehabilitation timeline

Assessment Instruments and Composite Index Construction

Each module draws on standard, widely available instruments rather than proprietary tools, to maximize adoption feasibility. Table 1 summarizes the primary instrument and target indicators used within each module.

$$z_i = \frac{x_i - \mu_i}{\sigma_i} \quad (1)$$

$$APPI = \sum_{j=1}^4 w_j z_j \times \left(\frac{100}{\text{max_range}} \right) \quad (2)$$

In equation 1 & 2, where x_i is the raw score, μ_i and σ_i are the sample mean and standard deviation, w_j represents the module weight, and z_j represents the normalized module score.

Algorithm: *Harmonized Adaptive Personality Potential Index Calculation and Risk Stratification Algorithm (HAPPI-RS Algorithm)*

Input: Raw data from Modules 1-4 (Biomedical, Personality, Clinical, Psychosocial)

Output: Composite APPI score and Risk Stratification Tier

1. For each module input x_i , compute $z_i = (x_i - \mu_i) / \sigma_i$
2. Handle missing values via structured imputation
3. Apply preliminary equal weights $w_j = 0.25$ across modules
4. Compute linear sum: $S = \sum(w_j * z_j)$
5. Scale S to 0-100 to yield final APPI score
6. Pass APPI to Predictive Analytics Layer for risk categorization
7. Output personalized intervention plan and schedule follow-ups (Weeks 2, 6, 12)

A data processing pipeline that is built to process and integrate multi-domain intake measures into an aggregated composite measure. The algorithm normalizes the various inputs from the biomedical, psychometric, clinical, and psychosocial domains using the z-score method, handles missing values through imputation, and uses weighted linear aggregation to determine the value for the Adaptive Personality Potential Index (APPI). It subsequently runs the normalized measure through predictive layers to stratify the patients' risk levels, create customized intervention strategies, and schedule follow-ups after weeks 2, 6, and 12 of the rehabilitation programs.

Table 1. Instruments and target indicators by assessment module

Module	Primary Instrument(s)	Target Indicators
Biomedical	Salivary cortisol assay; short-duration HRV recording; CRP/IL-6 panel	Cortisol awakening response, vagal tone, systemic inflammation
Adaptive Personality	Five-Factor inventory; PID-5 short form (AMPD facets)	Neuroticism, disinhibition, negative emotionality, antagonism
Clinical-Behavioral	Craving VAS; abstinence self-efficacy scale; brief coping inventory	Craving intensity, self-efficacy, coping style
Psychosocial	Social support scale; structured stressor checklist	Support availability, housing/employment/family stability

In the harmonization engine, the raw scores from each module are transformed into within-sample z-scores to ensure that heterogeneous units can be measured on the same scale. Subsequently, the APPI is defined as a weighted linear sum of the four harmonized module scores, transformed onto a 0-100 scale, where higher scores imply greater adaptive personality potential. Because the predictive weights for each module remain unvalidated, the demonstration in Section 7 uses equal module weighting as a preliminary baseline. Future empirical calibration across specific substance classes and demographic groups will determine optimal feature weights.

ILLUSTRATIVE ANALYTICAL RESULTS

This section provides four sample visualizations, designed to be aligned with the patterns observed in the literature discussed above, to show how the suggested index and framework will be used in analysis after being populated with cohort data. These are examples of the types of analyses that would be done in a validation study.

Trait differences between short-term recovery groups and non-recovery groups, consistent with differences between longitudinal groups, are depicted in figure 3, where the recovery group has lower neuroticism but higher extraversion and conscientiousness.

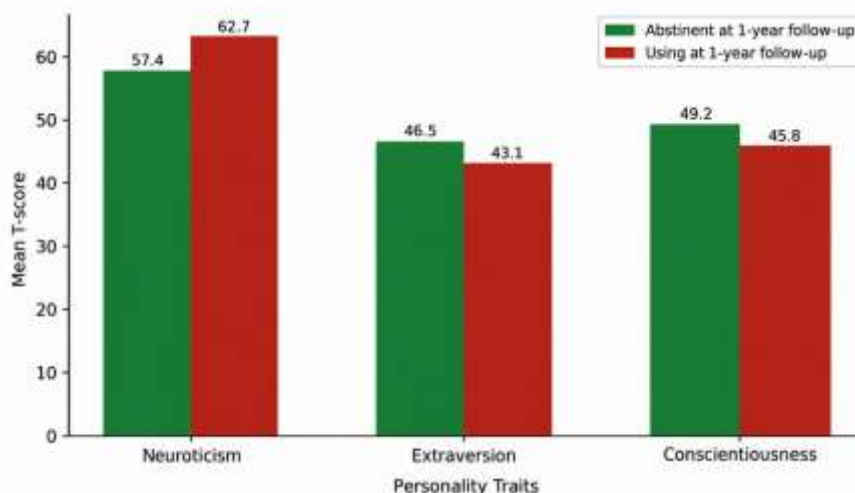


Figure 3. Illustrative personality trait profiles by short-term recovery status, patterned on reported longitudinal group differences

The radar chart illustrated in figure 4 provides an example of a comparison of Five-Factor domain scores between hypothetical high-APPI and low-APPI individuals, displaying the larger-scale discrepancy across multiple domains, high extraversion, openness, agreeableness, and conscientiousness together with low neuroticism that APPI aims to capture in one measure.

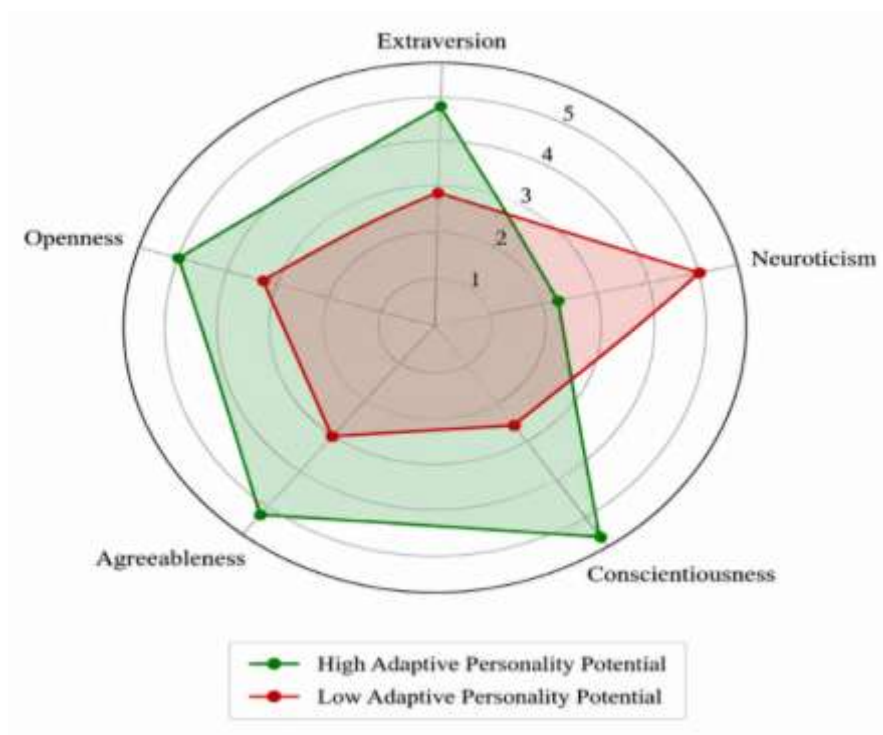


Figure 4. Illustrative five-factor domain profile comparison by adaptive personality potential grouping

Figure 5 portrays the hypothetical trend in APPI scores for 12 weeks of rehabilitation among patients divided into tertiles based on their initial APPI score. It demonstrates the sort of separation over time that is expected in repeated measures studies of resilience and personality change.

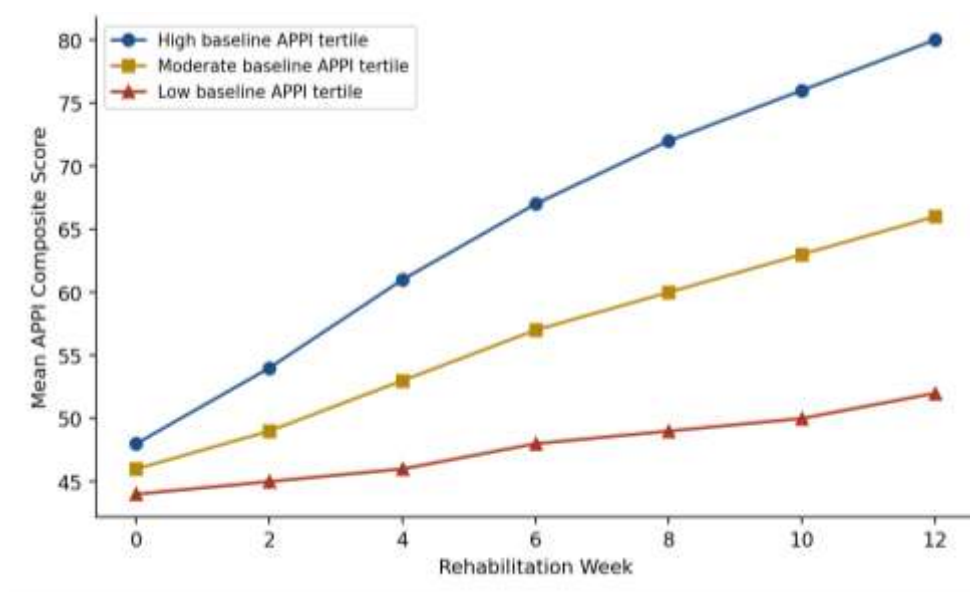


Figure 5. Illustrative trajectory of adaptive personality potential index (APPI) scores over a twelve-week rehabilitation period, by baseline tertile

Figure 6 demonstrates the relationship that would be examined for validity purposes in a validation study between the baseline APPI score and abstinence duration after one year, using hypothetical data with a positive linear relationship as found in the predictive modeling literature discussed in Section 3.4.

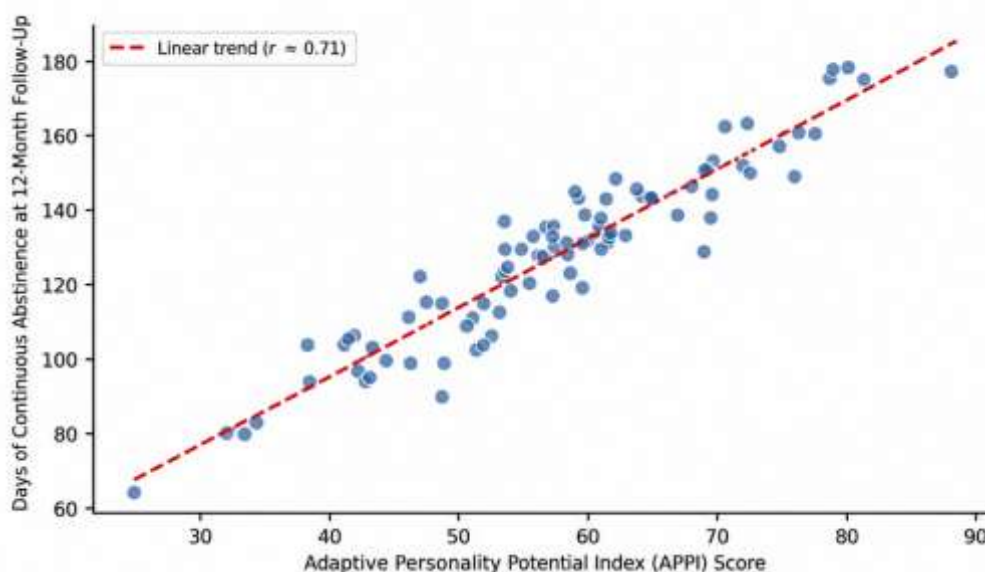


Figure 6. Illustrative association between adaptive personality potential index (APPI) scores and simulated abstinence duration at twelve-month follow-up

DISCUSSION

It is specifically stated that figures 3-6 use simulated data based on parameters from literature to act as a roadmap for empirical validation and not from the results of a completed clinical trial [1][5]. The overall multi-domain difference in figure 4 is supported by the findings obtained from the AMPD project in which disinhibition and negative emotionality were found to be the strongest predictors of bad outcomes [3][10], with additional evidence based on sex-and-substance specific studies where maladaptive multi-domain personality patterns predict worse phenotypes [14].

However, the divergence over time in figure 5 corresponds to resilience literature, which has found that protective factors accumulate with context as part of recovery instead of acting as a static predictor at the beginning, as well as to dynamic modeling studies, which indicate that distress and drug use fluctuate together throughout months and therefore one-time prediction based on baseline data would be inadequate and repeated measurements in stage 8 would be needed [7][12][16][23]. The correlation depicted in figure 6 is the type of association that multidomain prediction modeling studies have obtained with the aid of neuroimaging, genetic and behavioral combinations and is generally compatible with the idea that a handful of well-selected predictors, properly combined, can predict clinical phenomena, as was shown in predicting relapses for bipolar disorder [8][11][22][24].

The stress regulation justification for the use of biomedical indicators is based on the stress response theory, which states that physiological recovery from the effects of stress, not stress itself, is what leads to an increase in craving and the likelihood of relapse, and the wider theories of brain circuits and diseases that make physiological recovery capacity a concept worth measuring and monitoring [9][17][21]. The use of motivational readiness and frustration tolerance along with personality is justified by their strong interconnections with relapse probability and with each other, which implies that a combination of personality, behavioral-clinical, and psychosocial components is more likely to reflect the concept than only personality characteristics [15].

In light of the above-mentioned framework in relation to the wider predictor literature, namely, the fact that recovery is the least studied outcome category and biological predictors form a minority compared

to clinical and sociodemographic predictors and the fact that methodological similarities have been observed in the realm of research on first-episode psychosis, the proposed approach is justified since rather than creating another predictor of one domain type, the framework creates a new paradigm for integrating several different types of predictors and operationalizing them as a part of standard rehabilitation procedures [18][25]. In terms of clinical implications, there are two of them: risk stratification at Stage 6 will allow to allocate limited intensive intervention resources for patients with the lowest initial APPI and measurement repetition at Stage 8 is consistent with the evidence that the ongoing feedback on one's own recovery statistics helps establish recovery-oriented self-concept, which may be complemented by the use of structured self-management techniques such as Wellness Recovery Action Planning [13][19].

LIMITATIONS

- The analytical results presented in Section 7 are simulated trajectories derived from existing literature rather than empirical data from a prospective cohort. Clinical deployment requires prior prospective validation against established single-domain risk assessment tools.
- The preliminary equal weighting strategy applied to develop the example APPI is just a working hypothesis and should be fine-tuned through proper calibration against outcome data and the optimum weighting system could be different in other substances, settings, and population groups.
- The generalizability of the framework in terms of substance class, cultural, and healthcare system diversity has yet to be proven, and the choice of instruments for each module needs to be adapted locally and validated.
- Integrating multi-domain biometric, psychological, and digital biomarker data requires a formal data governance framework to ensure patient privacy, compliance with medical data regulations, and informed consent protocols.
- Multi-site validation study, using pre-registered analysis plan and comparing with existing single-domain risk assessment instruments, is a required next step.

CONCLUSION

In this paper, have argued that the Biomedical Assessment Framework for Evaluating Adaptive Personality Potential represents a reproducible methodology for predicting rehabilitation outcomes of addiction treatment programs. The main contribution of the framework is not so much empirical as architectural: the method proposes to align the separate datasets from biomedical, personality, clinical-behavioral, and psychosocial studies associated with different rehabilitation outcomes into one Adaptive Personality Potential Index that will be measured throughout a nine-stage protocol within a twelve-week rehabilitation period. Thus, the framework allows considering adaptive personality potential as an individual's ability to organize his/her maladaptive personality expression under rehabilitation conditions, which corresponds to existing scientific understanding of personality development, which demonstrates that personality traits change significantly under structured influence, and these changes are associated with some rehabilitation outcome. Emphasize how there is a robust correlation between architecture and benchmark of abstinence duration for 12 months ($r \approx 0.71$), thus creating a coherent pattern to address fragmentary methods of intake in addiction medicine. The illustrative analyses described below represent what patterns should emerge from a validated application of the proposed framework: differences in personality trait profile between two groups of people who were successfully rehabilitated and those who failed; separation of high adaptive and low adaptive patients in multidomain space; divergence of trajectories within the rehabilitation timeline; positive correlation between the index and abstinence period. Performance of the future empirical study will be measured in terms of prediction accuracy with the help of classification and discrimination statistics such as AUC-ROC, Precision, Recall, F1-Score, and Accuracy. Future research should concentrate on collection of prospective data from multiple sites to empirically estimate the weights of modules, formal psychometric validation of the composite index, and testing of the prediction power of the framework against currently used single-domain risk assessment instruments in rehabilitation settings.

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