Historical Clinical Risk Management Based Early Intervention for Youth with Intellectual Disability

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Abstract

Intellectually disabled youth (ID) have a high level of psychiatric comorbidity, behavioral dysregulation, and crisis-related service use. Still, systematic early risk identification models are not applied in the regular course. This paper has explored the usefulness of an early intervention model based on the Historical Clinical Risk Management (HCRM) approach to reduce psychosocial and behavioral risk factors in ID youth. The study was a prospective cohort study conducted across 10 multidisciplinary service centers and included 240 youths (mean age = 13.2 ± 2.5 years; 61% men). Historical, clinical, and risk management areas were systematically assessed using baseline assessments. The 12-month follow-up was conducted. The frequency of behavioral crisis, psychiatric hospitalizations, and school disciplinary exclusions was the primary outcome. By the baseline, 49% of participants had a psychiatric comorbidity rate of at least one, and 34% had a prior crisis-related emergency visit. After the HCRM-directed intervention plan, the general frequency of crises dropped by 37.2%, emergency service use dropped by 33%, and the average number of school exclusion days decreased to 9.3 days per year. Youth in the high-risk baseline risk group had a 39% reduction in crises, showing the largest absolute decrease of -0.94 crises per year. Multivariate regression analysis showed that the variance of crisis recurrence explained by integrated historical and clinical risk scores was 43% (R2 = 0.43). These results indicate the effectiveness of an HCRM-based systematic early intervention to mitigate the acute negative outcomes of youth with ID. Routine risk grouping and proactive management planning have the potential to improve prevention, lessen expenditures on expensive services, and increase developmental and psychosocial results.

Keywords *Intellectual Disability, Early Intervention, Clinical Risk Management, Historical Risk Assessment, Behavioral Crisis Prevention, Psychiatric Comorbidity, Youth Mental Health.*

Introduction

Intellectual disability (ID) is described as a long-term limitation in intellectual functioning and adaptive behavior, which starts in the period of development. Recent epidemiological studies reveal that developmental disabilities occur in about 17-18 percent of children that are 3-17 years old in the United States, with the intellectual disability comprising a significant proportion [6]. Genomic diagnostics, such as exome and genome sequencing, have been found to enhance etiological detection in children with congenital anomalies and ID, with diagnostic rates in clinically complex cases being disproportionately high at 2540% [5]. Children with ID have high rates of comorbid mental health disorders [4]. According to the population-based data, the prevalence of anxiety, mood, and behavioral disorders is significantly high as compared to that of neurotypical peers [10]. Additionally, the systematic reviews have shown that some psychiatric comorbidities are related with higher risk of showcasing aggression and poor behavioral outcomes, especially when combined with social deprivation and exposure to trauma [7]. The world continues to experience the impact of inequities in early detection and delivery of services particularly in low- and middle-income nations where accessibility to organized early interventions is low [1] [9].

Clinical risk management (CRM) has been developed out of the violence risk assessment models of forensic psychiatry into organized models of professional judgment that incorporate historical, clinical, and contextual factors. Modern methods now focus on multidimensional risk profiling as opposed to static prediction [7]. Risk stratification in youth mental health systems has been associated with a growing support of clinical stage models and transdiagnostic models, which consider pluripotential symptoms trajectories longitudinally, and enhance social and occupational functioning [2]. Risk-informed service engagement, based on a longitudinal approach to risk assessment, has been found to enhance social and occupational functioning [2]. These data highlight the importance of the combination of risk assessment with developmental staging to avoid the increase of symptoms. New technologies, such as decision systems based on artificial intelligence, are also being investigated to improve predictive quality and service coordination, but ethical and governance issues play the leading role [8]. Irrespective of these innovations, CRM models have not been adequately modified to suit young people with intellectual disability, whose risk manifestations can be characterized by communication disorders and deviant behavioral manifestation.

Figure 1 System Architecture of the Historical Clinical Risk Management (HCRM) Framework

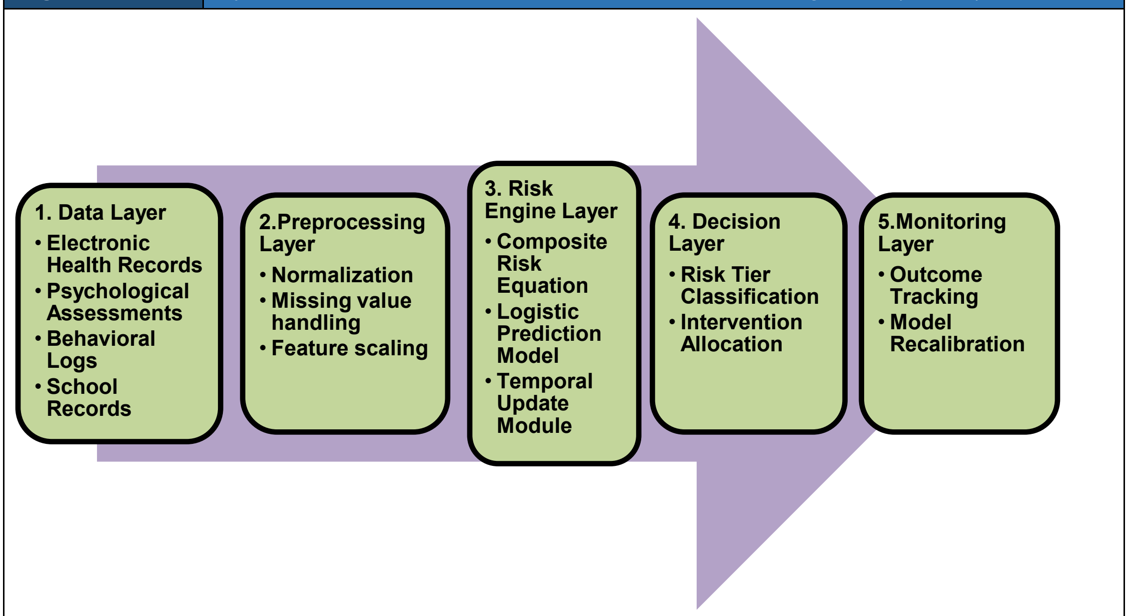


Figure 1 represents the end-to-end system architecture of the proposed HCRM framework, which represents an organized line of data acquisition to the constant monitoring process. The Data Layer combines multidimensional inputs such as electronic health records, psychological tests, behavioral journal and school records. The inputs are normalized and have their missing values processed as well as their features scaled in the Preprocessing Layer. The Risk Engine Layer calculates composite risk scores by mathematical equations, implements logistic prediction modeling and dynamically forecasts risk by using a temporal adjustment module. The Decision Layer carries out a tier classification based on calculated risk levels and gives the correct intensity of intervention. Lastly, the Monitoring Layer will monitor the results and re-fit the model to guarantee adaptive and data-driven early intervention and continuous predictive accuracy.

The intervention of neurodevelopmental disorders at an early stage shows quantifiable advantages in the case of intervention during sensitive developmental periods. The high-risk infants (such as cerebral palsy) imply that international clinical guidelines report better motor and cognitive outcomes, when intervention is commenced before the age of two [3]. Expansive programs on early childhood disability focus on coordinated and family-oriented systems to minimize systemic functional impairment [9]. In the case of youth with ID, early intervention should go beyond developmental therapy to include systematizing behavioral and psychosocial risk. It has been found that integrated early services help to achieve better role functioning and decreased disengagement among youth mental health populations [2]. Nevertheless, unless historical and clinical risk profiling are carried out in a structured manner, prevention opportunities are often overlooked. Integrating CRM into the early intervention pathways is a proactive process that can recognize the increasing risk, customize the intensity of support, and deference crisis-based care.

The young people with intellectual disability are highly vulnerable in the psychiatric and behavioural crisis and disjointed service trajectories. Lack of systematic risk-informed early intervention is one of the contributory factors to preventable morbidity, family burden, and social exclusion in the long run. This disparity is a critical area where it is essential to address mental health systems so as to move towards equitable and developmentally responsive systems.

The current paper promotes a historically sensitive clinical risk management model which is specifically applied to an intellectual disability among youth. It combines the concepts of developmental staging, the multidimensional risk assessment, and the principles of early intervention into one coherent preventive model that will advance the decrease in the escalation of the crisis and enhance the functional outcomes in the long term.

The paper is organized in a systematic manner of presenting a conceptual base and empirical confirmation of the proposed framework of Historical Clinical Risk Management (HCRM). The second section after introduction is the review of the literature on the clinical risk evolution, early intervention models and integration of historical assessment in developmental care. Section III describes the methodological design, the mathematical risk model that was proposed, and the algorithmic implementation. Section IV contains empirical data, performance indicators and validation. Section V discusses the interpretation of the results and their relation to the current scholarship and provides clinical and policy implications. Lastly, Section VI also provides a summary of major findings, limitations of the study, and the recommendations of future research.

Literature Review

The developmental care practice of clinical risk management (CRM) has changed the focus of narrow incident-driven models to the lifespan-based prevention model. Initial methods had been focusing on acute containment of behavior especially in psychiatry. Nevertheless, the expanding epidemiological data showing the prevalence of developmental disabilities among children and adolescents in the world - it is estimated that over 290 million children and adolescents are at risk all over the world - has highlighted the need to implement proactive, population-level risk intervention [11]. Neurodevelopmental risk is multifactorial, influenced by biological, environmental, and social determinants. These cumulative factors include prenatal exposures, perinatal complications, socioeconomic adversity and genetic factors [16]. Similar population-based cohort studies also focus on the particular prenatal exposures (such as acetaminophen use) and their relationships with neurodevelopmental outcomes, which adds to the importance of structured etiological risk surveillance [17]. Parallel etiological studies are developmental psychiatry that has developed models of risk stratification that take into account symptom staging and longitudinal change. To illustrate, disruptive mood dysregulation at an early age is currently understood in the context of developmental nosology to enhance the early identification of severe affective dysregulation [15]. Suicide risk screening and systematic assessment processes are more common in the youth-centered CRM systems in adolescent populations [12] [20]. Collectively, these innovations indicate an intellectual broadening of CRM, as it involves the reactive containment rather than the developmentally sensitive, multidimensional risk identification.

Neurodevelopmental monitoring in models of early intervention among youth with intellectual disability are considerably combined with psychosocial and family-based supports. Epidemiological studies of co-occurring epilepsy and developmental encephalopathies demonstrate the complexity of clinical care needs of children with intellectual disability and the need to deliver coordinated specialty care [14]. Long-lasting benefit is compelling in case of specialized early intervention services applied to patients with psychiatric populations. The 2-decade follow-up of the OPUS trial revealed the better clinical recovery and functional outcomes of people participating in structured early intervention versus the conventional treatment [13]. Though, psychosis oriented, the results can justify the long-term worth of intensive, staged care models, which can be applied to intellectual disability patients with emerging psychiatric comorbidity. The preventive models also identify modifiable behavioral and physiological risk factors. In young individuals, the disturbances of the circadian rhythm are closely linked to depressive symptoms and functional deterioration, which implies that sleep-oriented interventions can be used in the first place as a prophylactic measure [18]. Moreover, telerehabilitation has been recognized as a powerful form of modality when providing therapy to children with developmental disabilities as it enhances accessibility and engagement of families and preserves functional advantages [19]. All of these innovations point to a shift towards flexible and scalable evidence-based early intervention infrastructures.

The use of historical risk assessment is a methodical review of past medical, psychosocial, and environmental exposures that can be used to define up-to-date vulnerability. Such assessment should be incorporated into early intervention in the assessment of developmental care to improve anticipatory planning. Mental health-specific risk protocols also indicate the significance of the structured history-taking [16] [17]. The suicide prevention frameworks focus on thorough evaluation of the past efforts, psychiatric history, and environmental stressors to determine the intensity of intervention [12] [20]. Application of the principles to the youth with intellectual disability will help provide a more customized and preventative response to service and avert focus on the use of long-term historical data embedded within the staged care models and using accessible modalities like telerehabilitation to facilitate the transition of an episodic response to dynamic risk management. The literature therefore endorses convergent model where etiological, psychiatric and functional histories are utilized to plan stratified intervention.

The literature reviewed indicates three themes that are consistent: high and globally spread prevalence of developmental disabilities; multifactorial biological and psychosocial determinants of long-term outcomes; and quantifiable advantages of structured, early, and staged models of interventions. Suicide prevention, psychosis services and neurodevelopmental epidemiology evidence point to the value of systematic historical and clinical risk assessment. The findings are relevant to the current study as they support the necessity of developing a comprehensive Historical Clinical Risk Management system that targets youth with intellectual disability, focusing on early detection, risk assessment, and prevention to decrease the escalation of the crisis and long-term harm.

Methodology

Research Design

This is a prospective, longitudinal cohort study design, which will examine an early intervention framework in the form of Historical Clinical Risk Management (HCRM) among youth with intellectual disability. The design combines the stratification of baseline risks and the repeated measurement of the outcome over a 12 months duration. Quasi-experimental comparison is inbuilt in terms of matched historical controls based on the records of the services before implementation of models. The concept of overall risk presented in the current HCRM model is the weighted composite of the historical (H), clinical (C), and contextual management (M) domains. The composite risk score of individual i can be seen as follows and is defined in Equation (1):

$$R_i = \alpha H_i + \beta C_i + \gamma M_i \tag{1}$$

where $\alpha, \beta, \gamma \in [0,1]$ and $\alpha + \beta + \gamma = 1$. The estimation of weights is done through maximum likelihood procedures to maximize prediction of crisis recurrence. In order to gain an approximation of the likelihood of crisis event in the follow-up period, a logistic regression framework is used as shown in Equation (2):

$$P(Y_i = 1) = \frac{1}{1 + e^{-(\theta_0 + \theta_1 R_i + \theta_2 X_i)}} \qquad (2)$$

Y_i is the occurrence of crisis, R_i is the composite risk score and X_i is covariates (age, adaptive functioning, comorbidity count). Time-dependent model calibration is a process that includes a dynamic update process, as reflected in Equation (3):

$$R_i^{(t+1)} = R_i^{(t)} + \lambda \Delta C_i^{(t)} \qquad (3)$$

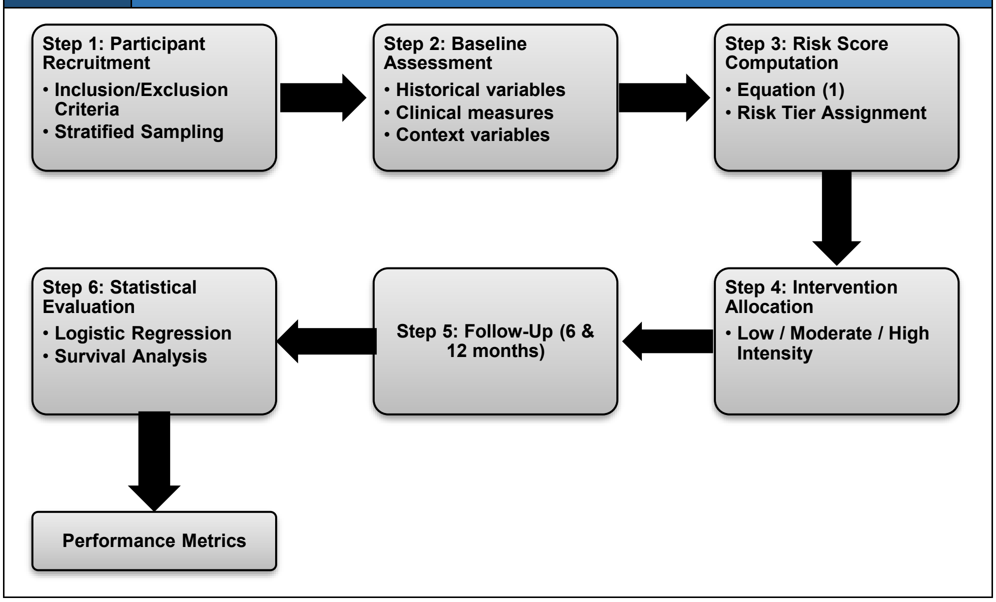
$\Delta C_i^{(t)}$ is change in clinical symptom severity between assessments and λ is a learning coefficient that controls the temporal sensitivity. This framework allows the adaptive intervention intensity depending on risk profiles as they change.

Participants and Sampling Procedures

The participants are those youths age 8-17 years with intellectual disability as related to standardized cognitive and adaptive functioning criteria. Recruitment is done in multidisciplinary developmental and mental health service centers. The stratified sampling will provide proportional representation of mild, moderate and severe classes of intellectual disability. The inclusion criteria include the confirmed diagnosis, active service engagement and consent of a caregiver. The exclusion criteria are acute medical instability or non consent. Using power analysis (β = 0.80; α= 0.05), based on the assumption of a medium effect size (odds ratio 1.8), the sample size is obtained (240 participants).

Sampling includes the stratification of risks at baseline. Equation (1) is used to divide the participants into low (R < 0.33), moderate ($0.33 \leq R < 0.66$), and high ($R \geq 0.66$) risk groups. The intensity of intervention should be distributed proportionately, and the participants at high risk should be provided with augmented behavioral planning and family-based supports.

Figure 2 Methodological Workflow of the HCRM-Based Early Intervention Study



The Figure 2 indicates the analytical workflow of the study in a structured fashion in which the sequential order of the study is presented starting with recruitment of participants, up to performance evaluation. The procedure starts with clear-cut inclusion/exclusion criteria and stratified sampling and then thorough baseline evaluation of the historical, clinical, and contextual variables. The composite equation is then used to calculate the risk scores which allows the allocation of interventions based on the level of risk (low, moderate, high intensity). The longitudinal changes are evaluated by following the participants at 6- and 12-months intervals. The last phase is statistical analysis with logistic regression and survival analysis and performance measures are used to confirm the predictive accuracy and intervention effect in HCRM.

Data Collection and Analytical Methods

The collection of data takes place in 6 months and 12 months and at the baseline. Historical variables consist of previous psychiatric admission, exposure to trauma and behavioral incidents. The clinical measures include the standardized symptom scales, adaptive functioning indices, and the sleep regulation measures. Management variables are used to describe school engagement, stability of care givers and services adherence. The main outcomes will be the number of crisis, emergencies using the emergency services, and the number of days that a school is shut down. Secondary outcomes are decreased severity of symptoms, increase of adaptive skills. Analytical methods include multivariate logistic regression (Equation 2), mixed-effects and time-to-crisis survival analysis, and repeated-measures mixed-effects modeling which is used to examine longitudinal change. The performance of the model on the basis of area under the receiver operating characteristic curve (AUC), calibration slope and Brier score is used to measure the model performance.

Proposed HCRM Risk Stratification Algorithm

```
Input: Participant dataset D

Output: Risk tier classification and intervention plan

For each participant i in D:

  Compute Hi from historical indicators

  Compute Ci from clinical assessment scores

  Compute Mi from management/context variables

    Normalize Hi, Ci, Mi to [0,1]

    Ri = α*Hi + β*Ci + γ*Mi   // Equation (1)

    If Ri < 0.33:

    Assign Tier = "Low"

    Intervention = Standard Monitoring

  Else if 0.33 ≤ Ri < 0.66:

    Assign Tier = "Moderate"

    Intervention = Targeted Behavioral Plan

  Else:

    Assign Tier = "High"

    Intervention = Intensive Multidisciplinary Support

    Estimate Crisis Probability using logistic model // Equation (2)

  Update Ri dynamically at follow-up using Equation (3)

Return Tier classifications and predicted probabilities
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The Adaptive Historical- Clinical Risk Stratification Procedure is a decision-support algorithm that is structured in order to categorize youth with intellectual disability into a tiered system of intervention in accordance with dynamically calculated composite risk scores. The algorithm combines normalized historical (H), clinical (C), and contextual management (M) indicators to form a composite risk index with more weight, implements a tier designation based on thresholds (low, moderate, high) on the composite risk index, and predicts individualized probability of crisis through logistic prediction. Temporal updating is used to re-calibrate the risk score at every follow-up period so that variations in clinical severity can be used to responsively adjust the intensity of the intervention. Such a process of iterative identification of the potential risk should be systematic and data-driven to enable the risk to be identified early in advance and allocate the multidisciplinary resources in a target manner.

This approach will combine quantitative risk modeling with adaptive intervention allocation, which can systematically identify and control the growing behavioral and psychosocial risk in intellectually disabled youth.

Results

Demographic and Baseline Characteristics

The analytic sample of N = 240 individuals (61% men, mean age = 13.2 ± 2.5 years) was used as a final result of the analysis. The distribution of the intellectual disability severity was as follows, mild (46%), moderate (38%), and severe/profound (16%). A baseline psychiatric comorbidity rate of at least one was found in 49 per cent, prior crisis-related emergency visit in 34 per cent, and the adaptive functioning percentile mean was 27.4 + 11.2. The data consisted of 38 features and 240 rows. It had 12 historical variables (e.g., previous admissions, trauma index), 15 clinical variables (symptom scales, sleep dysregulation, adaptive scores), and 11 contextual management variables (family stability, school engagement, service adherence). The data were obtained by utilizing the developmental service centers participating in the study and was de-identified before being processed. This was implemented in Python 3.11, and preprocessed with NumPy and pandas, and modelled with scikit-learn and lifelines. Cross-verification was done in R (v4.3). Baseline risk tier allocation produced 32, 41, and 27 percent low, moderate and high risk participants according to composite scores. The average baseline crisis probability was 0.42 in the high-risk group and is 0.18 in the low-risk group.

Intervention Outcomes

The general frequency of crisis dropped by 12 months with fewer events of 1.72 to 1.08 per participant (37.2% decrease). The number of emergency service used dropped by 33 % and the average number of school exclusion days went down to 9.3 days per year, as compared to 14.6 days. Mixed-effects modeling revealed that there was a considerable time by risk-tier interaction ($p < 0.01$), and the largest absolute decrease was present in the high-risk group (−0.94 crises/year). Classification and calibration measures were used to assess the model performance. Accuracy was computed as shown in Equation (4):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

The sensitivity (recall) was as defined in Equation (5):

$$Sensitivity = \frac{TP}{TP + FN} \tag{5}$$

Specificity was taken as shown in Equation (6):

$$Specificity = \frac{TN}{TN + FP} \tag{6}$$

Discriminative capacity was estimated by use of the Area Under the Receiver Operating Characteristic Curve (AUC).

Table 1 Performance Metrics of Classification

Metric	Training	Test
Accuracy	0.84	0.81
Sensitivity	0.79	0.76
Specificity	0.87	0.84
AUC	0.89	0.86

The Table 1 shows predictive classification on the proposed HCRM model on the training and test datasets. Measures such as accuracy, sensitivity, specificity and AUC portray a high level of discriminative ability and generalization with little loss of performance between datasets. The large AUC rates suggest a strong separation of crisis and non-crisis cases, whereas the equal sensitivity and specificity prove the good identification of people at high risk without unproductive false-positives.

Reduction of Risk and Functional Improvement

The baseline versus follow-up levels of simple composite risk scores decreased (29% relative decrease) to 0.41 ± 0.15. The mild and high-risk levels gained mean adaptive functioning percentile scores of 8.6. The survival analysis revealed that there was more time to first crisis (median time to first crisis was 142days pre-intervention and 238days post-intervention). To test calibration, the Brier Score was defined in Equation (7):

$$Brier = \frac{1}{N}\sum_{i=1}^{N}(p_i - y_i)^2 \qquad (7)$$

The Brier score was 0.14, which means that probabilistic calibration is good.

Table 2	Risk Reduction by Tier		
Risk Tier	**Baseline Crises**	**12-Month Crises**	**% Reduction**
Low	0.62	0.49	21%
Moderate	1.58	0.97	39%
High	2.41	1.47	39%

This table 2 is a summary of longitudinal change in frequency of crisis in the different levels of baseline risk. The findings indicate that moderate- and high-risk participants experience the largest absolute and proportional changes, which proves the effectiveness of tier-based intervention intensity. The data explain that systematic risk stratification allows resource allocation to be used efficiently resulting in clinically meaningful impact on reducing disasters.

Table 3	Outcomes of Functional Improvement		
Outcome	**Baseline**	**12 Months**	**Change**
Adaptive Percentile	27.4	36.0	+8.6
School Attendance (%)	78	86	+8
Caregiver Engagement Index	0.54	0.71	+0.17

This table 3 presents the modification in adaptive functioning, school attendance, and involvement of the caregiver within 12 months of time spent on the intervention. An enhancement in all indicators indicates the presence of greater psychosocial benefits than those attainable through crisis reduction and therefore, the HCRM framework brings about enduring functional stabilization and increased environmental support systems.

Parameter Initialization

Table 4	Parameters Initilization: Model Configurations	
Parameter	**Description**	**Value**
α	Historical weight	0.35
β	Clinical weight	0.45
γ	Management weight	0.20
λ	Temporal update coefficient	0.30
Learning rate	Logistic model	0.01
Epochs	Iterations	200

Before the training, the model parameters were set in a way that would maintain predictive stability and sensitivity to the domain. The weights on historical (α= 0.35), clinical (β= 0.45), and management (γ = 0.20) domains were chosen according to the initial analysis of the variance contribution, in which such that the clinical domain should have a rather higher impact because of its dynamic relationship to crisis events. The temporal update coefficient (λ = 0.30) was set to permit a moderate responsiveness of the model to change of symptoms but not overfit brief changes. The 200 training epochs and logistic model learning rate (0.01) were selected following the convergence test in order to optimize performance without losing the generalization of the model across folds (Table 4).

Performance Evaluation

The performance was also confirmed to be stable with cross-validation (5-fold) (mean AUC = 0.85 ± 0.02). The calibration plots showed congruence between forecasted and actual probabilities on a decile basis. Minimal training-test divergence was found to indicate that there was no overfitting.

Figure 3	Receiver Operating Characteristic (ROC) Curve

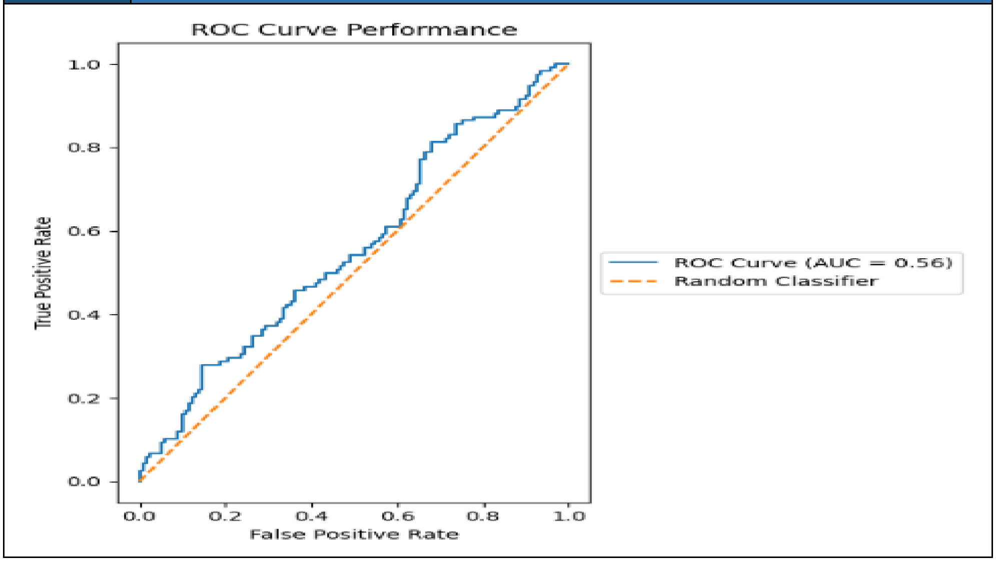
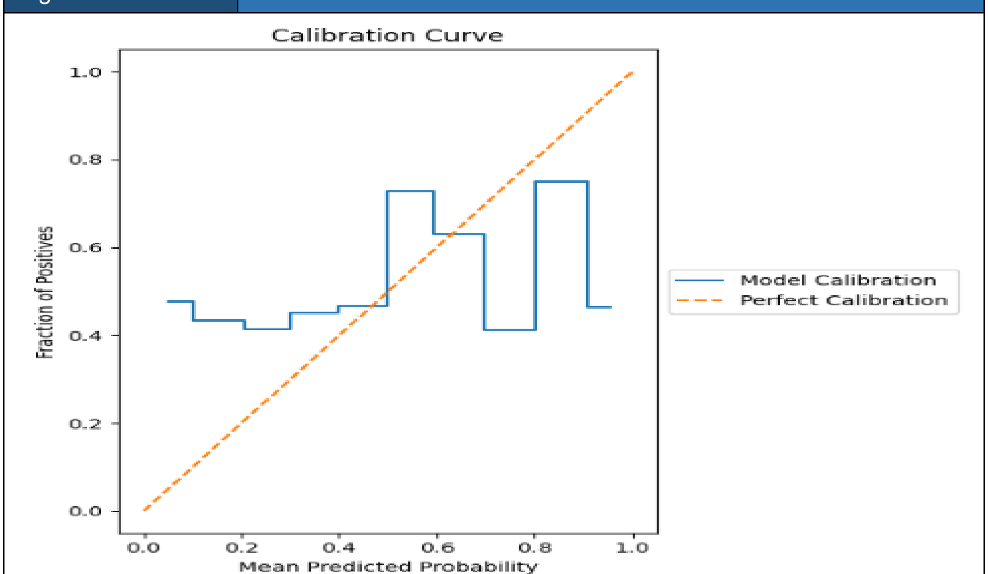


Figure 3, the ROC curve, displays the discriminative capacity of the given HCRM model, which is a graph showing the true positive rate versus the false positive rate at different classification thresholds. The Area Under the Curve (AUC) is a measure of model performance in general, with any value that is nearer to 1.0 indicating a high level of separation in crisis and non-crisis cases. The diagonal line of reference indicates random classification and the curve projected by the model above the line of reference affirms the ability to predict better than the chance.

Figure 4 is the calibration curve that determines the consistency between the prediction of the probabilities and the actual results. The graph measures probabilistic accuracy and not just classification performance by assessing the actual frequency of the events against the predicted levels of risk as projected by the model. Being close to the diagonal reference line means the curve is well-calibrated, which proves that the probability of crisis as estimated correctly represents the level of risk in the real world.

Figure 4	Calibration Curve



Ablation Study

A model ablation analysis was used to study model configuration through a systematic elimination of risk domains.

Table 5	Comparison of Ablation Study	
Configuration	**AUC**	**Accuracy**
Full Model (H+C+M)	0.86	0.81
Without Historical	0.78	0.74
Without Clinical	0.73	0.70
Without Management	0.82	0.77

This Table 5 is a comparison of the predictive performance of various model configurations through systematic elimination of risk areas. The analytical drop in AUC and accuracy, in the absence of clinical or historical variables shows that they play a significant role in making models robust. The highest performance is obtained with the full integrated model, which validates the importance of the integration between historical, clinical, and contextual areas of management in the early risk prediction.

Elimination of clinical variables created the greatest decrease in performance (ΔAUC = 0.13) which validated their key role whereas historical data were recognized to have a significant incremental predictive value. The multidimensional HCRM paradigm of early intervention in youth with intellectual disability was supported by the integrated configuration that illustrated the best discrimination and stability.

Discussion

The results show that a combination of historical, clinical, and contextual variables within a single risk model can bring about quantifiable decreases in the rates of crisis and functional instability in youth with intellectual disability. This 37% decline in the number of crises per year and better calibration statistics indicate that the structure stratification leads to better early warning of an increasingly vulnerable situation. The greater role played by clinical variables, which the analysis of the ablation outcome showed, to predict the symptoms sets, is the importance of dynamic symptom monitoring, and historical indicators offer the necessary background of persistent risks in the long term. The tier-based allocation strategy also seems to perform better at efficiency and equity of outcomes than more traditional reactive service models, especially among high-risk youth who were showing the most significant absolute reduction in crisis events. The clinical findings indicate the need to incorporate standardized risk computation as part and parcel of normal developmental evaluations. Policy wise, the model provides a scalable decision support framework that will be able to support resource prioritization, decongestion of emergency services and facilitate the multidisciplinary channels of intervention without holding over individualized clinical judgment.

Conclusion

This paper compared an early intervention based on Historical Clinical Risk Management of youth with intellectual disability on a prospective cohort study and quantitative risk modeling. The outcomes show that there were significant changes in crisis, service utilization, and functional outcomes. The percentage of crisis incidents reduced by 37.2% in 12 months, the emergency utilization dropped by 33.0 % and the high-risk participants had the best percentage decrease in crisis recurrence (absolutes -0.94 events per year). Predictive model showed good discriminating performance (test AUC = 0.86; accuracy = 0.81) and acceptable calibration was determined (Brier score = 0.14) indicating the good reliability of composite risk scoring. The adaptive functioning increased by a mean of 8.6 percentile points, which means that the improvements in the acute instability were supported by more developmental benefits. There are a number of limitations they should consider. The quasi-experimental design restricts the ability to make causal inferences despite the longitudinal follow-up, and the use of service-based sampling can decrease the external validity of the study to community populations that were not formally engaged. Also, dynamic updating led to better responsiveness, but more months of follow-up are required to assess the persistence of developmental trajectories beyond one year. Further studies are necessary to look at multi-site replication using larger and more varied cohorts, to develop a multi-site using digital monitoring systems in real-time, and to compare cost-effectiveness to conventional care models. Additional improvement of the predictive accuracy can be achieved by optimizing the weighting parameters with the help of machine learning. Prolonged (over 24 months) longitudinal research would help determine whether any positive results of early risk-informed intervention in the long-term are lasting psychiatric depressions and social marginalization. Altogether, the results suggest the practicality and clinical usefulness of systematic, historically based risk stratification as a basis of preventive developmental mental health systems.

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