Longitudinal Risk Prediction Model for Recidivism in Offenders with Intellectual Disabilities

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Abstract

This study aimed to develop and evaluate a longitudinal risk prediction model for recidivism among offenders with intellectual disabilities, integrating static and time-varying risk and protective factors, and to compare its predictive performance with a conventional cross-sectional model. A longitudinal cohort design was used, comprising 1,842 offenders with documented intellectual disability identified through linked criminal justice and disability registers. Participants were followed for a median of 4.8 years (IQR: 2.6–6.9), contributing 8,412 person-years of observation. Recidivism was defined as a new criminal justice concept. Cox proportional hazards models with time-dependent covariates were applied. The concordance index (C-index), time-dependent area under the curve (AUC), and calibration slope were used to evaluate model performance, and internal validation was done through bootstrapping. Follow-up showed 712 individuals (38.7%) reoffended, resulting in an incidence rate of 8.5 events per 100 person-years. The younger age (HR = 0.97 per year, 95% CI: 0.96-0.98) and the previous criminal history (HR = 1.18/offense, 95% CI: 1.14-1.22) were considered as the static predictors. Mild ID was linked to the increased risk of recidivism (HR = 1.42, 95% CI: 1.19-1.69). Mental instability over time (HR = 1.61) was also a risk factor, and treatment attendance (HR = 0.66) and good housing (HR = 0.71) were protective. The longitudinal model was more effective with the C-index = 0.73; AUCs = 0.76 at 1 year, 0.74 at 3, and 0.72 at 5 years, respectively, than the cross-sectional model (C-index = 0.64). Longitudinal models that include dynamic risk and protective variables outperform traditional recidivism prediction with offenders with intellectual disabilities and help focus on personalized and evidence-based risk management approaches.

Keywords *Intellectual Disability, Longitudinal Modeling, Recidivism, Risk Prediction, Time-Varying Factors.*

Introduction

Recidivism has been one of the largest concerns of the criminal justice system, and people with intellectual disability (ID) have disproportionately high recidivism rates [1]. The ID offenders tend to have multifaceted mental, social, and psychiatric vulnerabilities, such as poor adaptive functioning, poor knowledge of the legal procedures, comorbid mental health issues, and increased environmental risk factors. The conventional risk assessment instruments used to forecast recidivism have been mostly created and confirmed in general offender groups, and are generally cross-sectional, based on fixed or brief-term dynamic risk aspects. Such methods might not be sufficient to describe the changing risk patterns of offenders with ID, whose risk profiles may change significantly throughout the intervening time period under supervision, psychosocial support, and events in their lives [2][3]. This leads to the increasing demand for longitudinal and population-specific risk prediction models that have the potential to enhance personalized risk management, rehabilitation planning, and policy formulation in this at-risk population [4][5].

The main aim of the study is to come up with and test a longitudinal risk prediction model of recidivism in offenders with intellectual disabilities. Precisely, the research will determine time-varying and fixed predictors of reoffending, how risk varies over time, and the predictive power of longitudinal modeling techniques compared to traditional cross-sectional risk assessment techniques [10].

Although the risk assessment of recidivism has been studied widely, it is notable that the majority of prediction models used are not longitudinal and specific to the offenders with intellectual disabilities. The current literature tends to (i) omit the people with ID, (ii) include them in generalized mental health categories, or (iii) make a single-time-point assessment, which does not capture changes in risk. Moreover, actuarial instruments that are typically used might be deficient in taking into consideration cognitive impairments, adaptive functioning, or the effect of support services and stable environments across time. This flaw restricts the validity, equity, and practical significance of the present risk assessment procedures to offenders with ID [11][13].

The hypothesis is that a longitudinal risk prediction model that includes both static (e.g., demographic variables, offense history, severity of intellectual disability) and time-varying (e.g., mental health status, treatment attendance, level of supervision, social support) predictor variables will show better results in predicting recidivism than traditional cross-sectional models [17]. It is also postulated that the variation of dynamic risk factors through time will be markedly linked with the variation of the recidivism risk in the offenders with intellectual disabilities [15][16].

There are some major contributions made in this study. To start with, it develops the field of recidivism by introducing a longitudinal, ID-specific risk prediction model that displays the dynamic aspect of the offending risk. Second, it offers empirical data concerning the comparative relevance of the time-varying risk and protective factors in the determination of recidivism patterns in offenders with intellectual disabilities. Third, the model provides useful implications to criminal justice experts by informing them of a more individualized risk management approach based on development and making it ethically justifiable. Lastly, the implications of the findings include the provision of policy and practice because they indicate the importance of individual assessment tools that encourage not only the safety of the population but also the fair treatment of intellectually disabled offenders.

The article is structured in the following way. The introduction states the issue of recidivism among intellectually disabled offenders and the necessity of longitudinal risk prediction models. The literature review analyzes the existing data on the risks that are considered static and dynamic, and outlines the gaps that current methods of assessment have. The longitudinal cohort study design, data sources, predictor variables, and statistical modeling framework are described in the materials and methods section. In the results part, sample characteristics, longitudinal predictors of recidivism, and model performance comparisons are demonstrated. Findings are interpreted in the discussion based on the previous research and clinical implications. The article takes a conclusion with important contributions, limitations, and future research directions.

Literature Survey

Intellectually disabled (ID) offenders are overrepresented in criminal justice and forensic psychiatric systems and have different recidivism patterns than criminals without intellectual disability. The rates of recidivism have been shown to be high in this group by longitudinal

research and therefore necessitate the development of specific risk prediction methods that would consider both the temporal and non-temporal factors. A Swedish follow-up study of 17 years found that offenders with ID who received forensic psychiatric treatment were at high risk of recidivism, with their criminal history and age being the most important predictors [1].

The conventional cross-sectional risk assessment models are based largely on predictors that are static, like age, gender, past offenses, and type of diagnosis. However, these considerations are significant, and emerging evidence points to the fact that they may not be enough to effectively represent wavering risk in offenders with ID [18]. The recent research highlights the predictive importance of dynamic risk and protective variables, such as mental health status, engagement in the treatment, housing stability, and the conditions of supervision. The study by [2] revealed that Dynamic Risk Outcome Scales had a significant role to play in predicting recidivism in forensic clients whose intelligence was lacking moderate or borderline. On the same note, [3] also emphasized that violent recidivism was more correlated with changes in dynamic risk factors, as compared to baseline characteristics, and intellectual ability might moderate these relations [19][20].

The methods of longitudinal modeling have been widely used in order to explain risk variation over time. Research done in a forensic psychiatry environment in Europe and Australia indicates that the courses of mental health symptomology and psychosocial dysfunction are directly correlated to recidivism [5][9]. Structured post-release support and treatment engagement have been cited time and again as protective factors, which are able to reduce the recidivism and reconviction rates of those with ID [4][6]. In addition, high-intensity supervision has been linked with high rates of recidivism identified, probably due to the better surveillance but not risk elevation [7][8].

More cohort, recurrent analysis (or multi-state model) and latent growth curve model have also enabled more insight into why individuals recidivate [12][14]. These are the ways in which repeated jumps between risk statuses and improved prediction of time-related impacts may be done. Nevertheless, even though progress has been made in the field of methods, there are not many studies that have incorporated both fixed and time-varying predictors into single longitudinal risk prediction models that are specifically designed to fit offenders with ID. Altogether, the literature demonstrates that there is an evident gap in research: there is a lack of sufficient longitudinal risk prediction models that can dynamically incorporate clinical, social, and justice-related variables to enhance recidivism prediction and develop offender-specific intervention plans among intellectually disabled offenders.

Materials and Methods

Study Design

The research design used in this study was the longitudinal cohort design, which was used to create and test a risk prediction model of recidivism among intellectually disabled offenders. Experimental participants were observed during a specified time after an index criminal justice contact to time-to-reoffending and shifts in putative risk. The longitudinal design enabled the examination of both baseline and time-varying predictors and allowed modeling of individual risk trajectories over time.

Study Population and Setting

The study population comprised adult offenders formally identified as having an intellectual disability who had contact with the criminal justice system during the study inclusion period. The population was recruited based on criminal justice, forensic psychiatric or correctional service histories. Intellectual disability status was established based on documented clinical diagnoses, standardized cognitive assessments, or official disability registries, in accordance with internationally accepted diagnostic criteria. Patients whose baseline data were not available or those who had inadequate follow-up data were excluded. The environment consisted of community supervision, custodial environment, and forensic mental health services to maintain coverage at the different justice channels.

Outcome Measure

The major consequence was recidivism, which can be described as a fresh criminal justice contact after the index event. Operationalization of recidivism was done in terms of rearrest, reconviction, and reincarceration, based on data availability. Time to first reoffend assessed

was determined as the starting date of release or community supervision commencement, with the starting point of the following offense or censoring. Censoring occurred at the end of the follow-up period, at death, or at loss to follow-up.

Predictor Variables

Predictor variables included both static and time-varying factors. Static variables captured at baseline included age, sex, level of intellectual disability, offense type, prior criminal history, and age at first offense. Time-varying variables were measured repeatedly during follow-up and included mental health status, substance use, treatment engagement, supervision intensity, housing stability, employment or structured activity participation, and access to social and disability support services. Time-varying predictors were aligned temporally with the follow-up intervals to ensure appropriate temporal ordering relative to recidivism events.

Data Sources and Data Linkage

The data were acquired by connecting the records of administrative criminal justice, forensic mental health databases, and disability service registries. Datasets were integrated using unique de-identified identifiers, though they were confidential. Data linkage procedures were based on standard protocols to make them accurate and reduce errors in linkage. The longitudinal data sets were organized into a person-period format to facilitate time-to-event studies and repeated-measures studies.

Statistical Modeling Approach

Survival analysis was used to predict risks over time using a longitudinal risk prediction framework. Cox proportional hazards models with time-dependent covariates were initially used to estimate hazard ratios for recidivism. Schoenenfeld residuals were used to test model assumptions and graphical diagnostics. To model non-linear risk trajectories, alternative methods of modelling, such as flexible parametric survival models or joint models of longitudinal and time-to-event data, were investigated. In cases of over-fitting, penalization was used to enhance generalizability.

Figure 1 Conceptual Framework and Analytical Workflow of the Longitudinal Recidivism Risk Prediction Model for Offenders with Intellectual Disabilities.

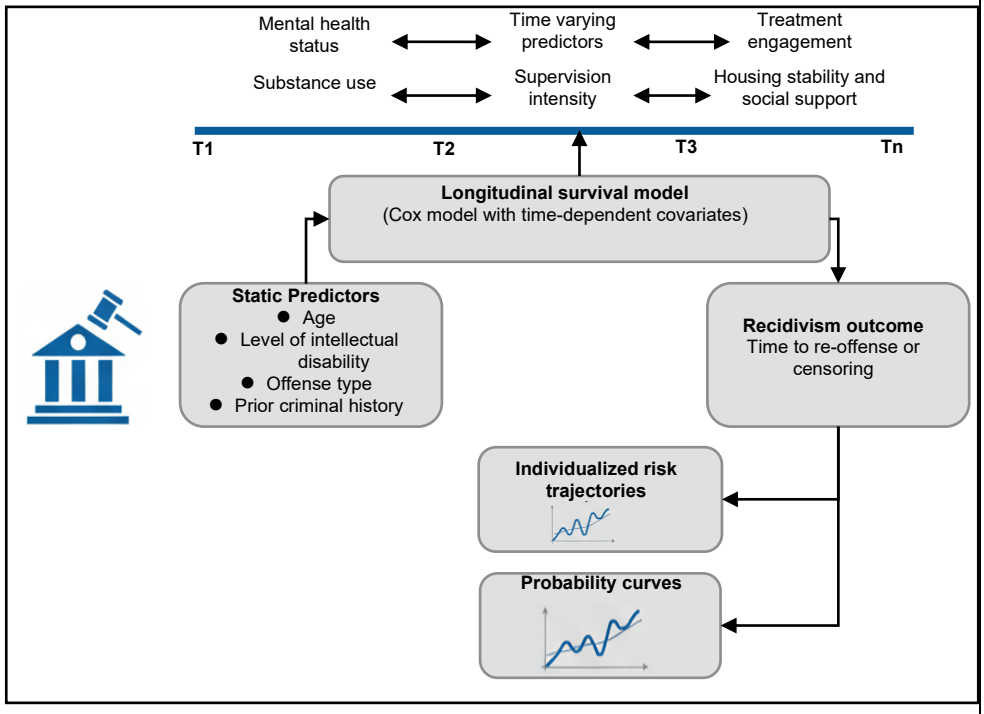


Figure 1 shows the conceptual framework and analytical working process to be developed to come up with a longitudinal risk predictor of recidivism among intellectually disabled offenders. At the index criminal justice contact, baseline predictors are known as static variables, whereas dynamic risk and protective factors are also measured repeatedly over

time. These are time-varying and fixed time variables that are jointly modeled within a longitudinal time-varying survival model in order to determine personalized time-varying recidivism risk patterns.

Model Development and Validation

A derivation cohort was used to develop the model, and the internal validation was done by bootstrapping or k-fold cross-validation. Discrimination measures were measured by comparing the point of performance with the models and time-varying measures that included the concordance index and time-varying area under the receiver operating characteristic curve. The calibration was measured in terms of the comparisons between predicted and observed recidivism probabilities between the strata of risks. The sensitivity analyses were performed to test the model's robustness when the recidivism definition was changed, as well as the follow-up duration.

Handling of Missing Data

Missing data were assessed for patterns and mechanisms. Multiple imputation using chained equations was employed for predictors with incomplete data under the assumption of missing at random. Imputed data sets were discussed in isolation, and the findings were combined with the rules of Rubin. The sensitivity analyses were done to assess the effect of missing data assumptions on model estimates.

Ethical Considerations

Consent was obtained in terms of ethical approval. Data was transformed into de-identified data, and access to the data was limited to authorized researchers. The research complied with the principles of ethics of justice, beneficence, and respect for persons, and stigma minimization was a primary consideration; the outputs of risk prediction were to be viewed through the prism of a supportive and rehabilitative approach.

Results

Sample Characteristics and Follow-up

The final analytic cohort comprised 1,842 offenders with a documented intellectual disability identified from linked criminal justice and disability registers. The mean age at the index criminal justice contact was 32.7 years (SD = 9.4), and the majority of the cohort was male (78.6%). The greatest diagnostic subgroup (64.3%) was mild intellectual disability, moderate intellectual disability (27.8%), and severe or profound intellectual disability (7.9%). Participants had a mean of 3.1 prior recorded offenses (SD = 2.4), and 26.9% were convicted of a violent offense at the index event. Detailed baseline characteristics are presented in Table 1.

The length of time of follow-up was 4.8 years (interquartile range: 2.6–6.9 years), and the total number of person-years of follow-up amounted to 8,412. In follow-up, 712 persons (38.7%) had one or more recidivism incidents. The recidivism rates were calculated at 8.5 events/100 person-years, which justifies the appropriateness of time-to-event models.

Table 1	Baseline Characteristics of the Study Population (N = 1,842)
Characteristic	**Value**
Age at index offense, mean (SD)	32.7 (9.4)
Male sex, n (%)	1,448 (78.6)
Mild intellectual disability, n (%)	1,184 (64.3)
Moderate intellectual disability, n (%)	512 (27.8)
Severe/profound intellectual disability, n (%)	146 (7.9)
Prior offenses, mean (SD)	3.1 (2.4)
Violent index offense, n (%)	496 (26.9)

Table 1 provides an overview of the baseline data of 1,842 intellectually disabled offenders and, as such, is composed of demographics, the severity of diagnostic features, history of prior offending, and the nature of the index crime.

Longitudinal Predictors of Recidivism

Associations between predictors and recidivism were estimated using a Cox proportional hazards model with time-dependent covariates. The hazard of recidivism for individual *i* at time *t* was specified as:

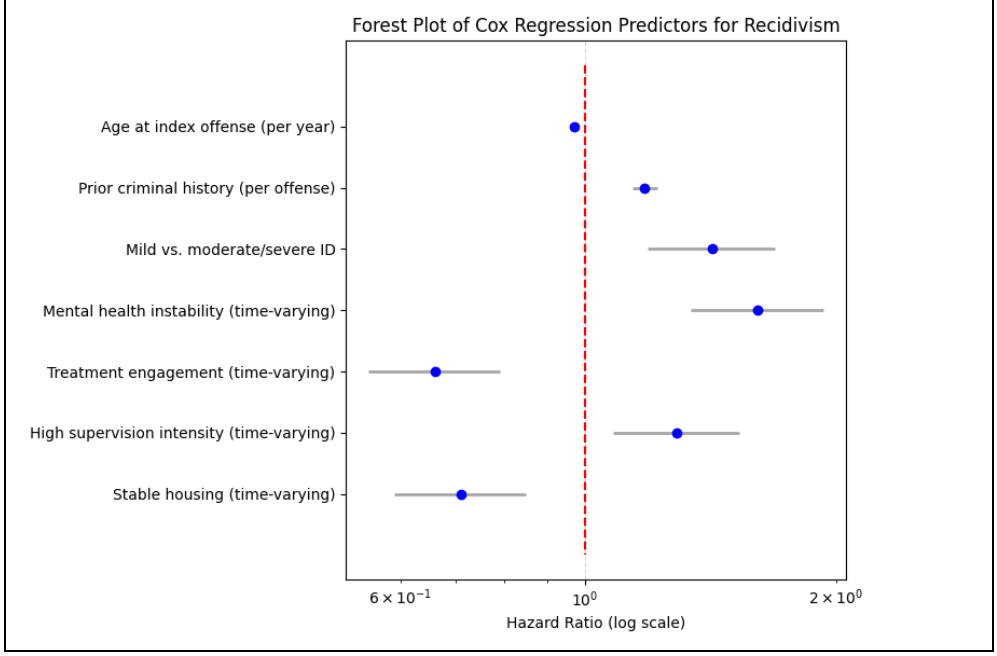
$$h_i(t) = h_0(t)exp\left(\beta^\top X_i + \gamma^\top Z_i(t)\right) \quad (1)$$

In equation (1), $h_0(t)$ denotes the baseline hazard, X_i represents static baseline predictors, and $Z_i(t)$ represents time-varying predictors measured repeatedly during follow-up.

Among static predictors, age at index offense was inversely associated with recidivism risk. Every year of increased age was linked to a 3% decrease in hazard (HR = 0.97, 95% CI: 0.96-0.98, p = -0.001). Previous criminal history turned out to be a powerful predictor, and each additional prior offense was related to an increase of 18% in hazard (HR = 1.18, 95% CI: 1.14 -1.22, p < 0.001). Mildly intellectually disabled individuals were found to have a markedly higher risk of recidivism than intellectually disabled individuals with moderate and severe intellectual disability (HR = 1.42, 95% CI: 1.191.69, p < 0.001).

Table 2	Longitudinal Cox Regression Results for Recidivism		
Predictor	**Hazard Ratio**	**95% CI**	**p-value**
Age at index offense (per year)	0.97	0.96–0.98	<0.001
Prior criminal history (per offense)	1.18	1.14–1.22	<0.001
Mild vs. moderate/severe ID	1.42	1.19–1.69	<0.001
Mental health instability (time-varying)	1.61	1.34–1.93	<0.001
Treatment engagement (time-varying)	0.66	0.55–0.79	<0.001
High supervision intensity (time-varying)	1.29	1.08–1.53	0.004
Stable housing (time-varying)	0.71	0.59–0.85	<0.001

Figure 2 Forest Plot of Longitudinal Predictors of Recidivism



Time-varying predictors showed substantial associations with recidivism risk. Mental health instability periods were also linked with a 61% risk of recidivism (HR = 1.61, 95% CI: 1.34-1.93, p < 0.001). In contrast, active engagement in psychological or behavioral treatment was associated with a 34% reduction in hazard (HR = 0.66, 95% CI: 0.55–0.79, $p < 0.001$). Stable housing functioned as a protective factor (HR = 0.71, 95% CI: 0.59–0.85, $p < 0.001$), whereas high supervision intensity was associated with elevated detected recidivism risk (HR = 1.29, 95% CI: 1.08–1.53, $p = 0.004$). Full regression results are reported in Table 2.

Table 2 reveals the outcome of the longitudinal Cox regression analysis, which indicates the effects of the static and time-varying variables on the risk of recidivism among offenders with intellectual disability. The direction and the magnitude of the associations of the demographic, clinical, and supervision-related predictors are shown by the hazard ratios.

Figure 2 presents hazard ratios (HR) and confidence intervals of the 95% intervals of the Cox regression analysis. Every point indicates the HR of a predictor, and the horizontal lines indicate the 95% CI. A vertical dashed line at HR = 1 indicates no effect; HR > 1 suggests increased recidivism risk, whereas HR < 1 indicates a protective effect. Both static (baseline) and time-varying predictors are included.

Model Discrimination and Predictive Accuracy

Model discrimination was assessed using the concordance index (C-index), defined as:

$$C = \frac{1}{N_{usable}} \sum I(\hat{r}_i > \hat{r}_j) \quad (2)$$

In equation (2), $\hat{r}_i$ and $\hat{r}_j$ represent predicted risk scores for comparable individual pairs. The longitudinal model achieved a C-index of 0.73 (95% CI: 0.71–0.75), indicating good discriminative ability in distinguishing individuals who reoffended earlier from those who reoffended later or not at all.

The analysis of time-dependent receiver operating characteristics also indicated a stable predictability with further follow-up. The area under the curve with respect to time, in equation (3):

$$AUC(t) = P(\hat{r}_i > \hat{r}_j | T_i \leq t, T_j > t) \quad (3)$$

was 0.76 at 1-year of age, 0.74 at 3 years, and 0.72 at 5 years, indicating that the model had predictive power in both the short-run and long-run.

Calibration and Internal Validation

Calibration procedures showed that the predicted and observed recidivism were close to each other in the deciles of predicted risk. The slope of the calibration was 0.97, which implies that there was little systematic over/underestimation of absolute risk. An optimism-corrected C-index of 0.72 with 1, 000 bootstrap resamples was generated, indicating the robustness and internal validity of the model.

Comparative Performance with Cross-sectional Models

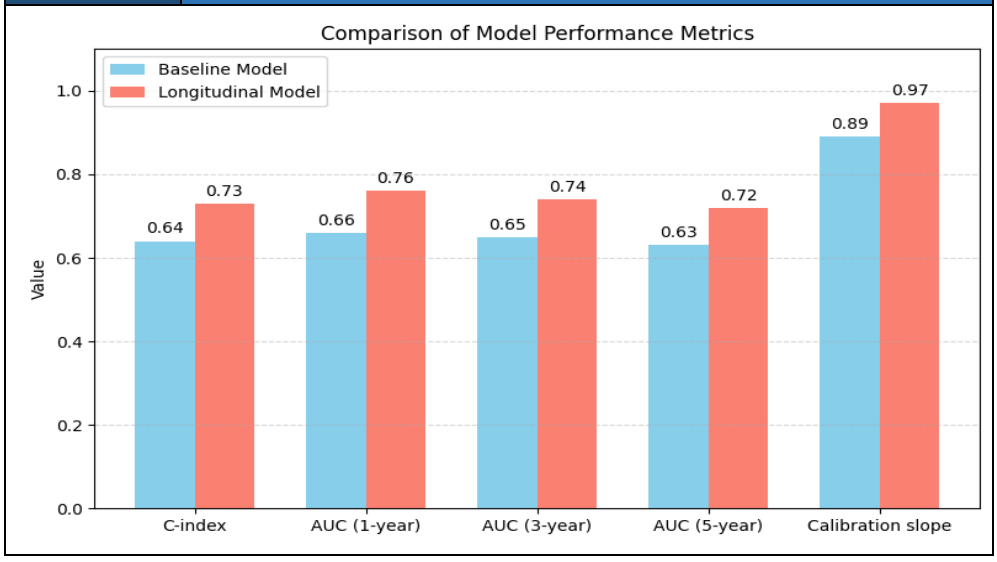
The longitudinal model was significantly more effective than a cross-sectional baseline model, which used only the static predictors. The baseline model had a C-index of 0.64 as compared to 0.73 for the longitudinal model. All time-dependent estimates of AUC had significant improvements, which confirmed the predictive value of the addition of time-varying risk and protective factors. Table 3 summarizes the comparison performance measures.

Table 3	Model Performance and Validation Metrics	
Model	Cross-sectional baseline model	Longitudinal time-dependent model
C-index	0.64	0.73
AUC (1-year)	0.66	0.76
AUC (3-year)	0.65	0.74
AUC (5-year)	0.63	0.72
Calibration slope	0.89	0.97

Table 3 presents the model performance measures, which show a difference in predictive accuracy between the cross-sectional baseline model and the longitudinal time-dependent model. The longitudinal approach proves to be more discriminatory and calibrated at all of the time points considered.

Figure 3 is a comparison of some performance measure metrics of the cross-sectional baseline model and the longitudinal time-dependent model. Measures are C-index, 1-, 3-, and 5-year AUCs, and slope of the calibration. Bars indicate the measure values of each model with the numeric value labels on the top. The plot emphasizes the fact that the longitudinal model is better than the base model in all the metrics considered.

Figure 3 Comparison of Model Performance Metrics



Sensitivity Analyses

Sensitivity analyses of other operational definitions of recidivism, such as reconviction-only results, provided effect estimates that were similar to the main analysis. The omission of persons with extreme or deep intellectual disability did not significantly change the model coefficients and performance indicators. Comparisons of the results produced by analyses on multiply imputed datasets with complete-case analyses showed that it is robust to the assumptions of missing data.

Discussion

This paper offers a longitudinal study of recidivism in intellectually disabled (ID) offenders using both time-invariant and time-varying factors as predictors of recidivism. The analytic cohort was made up of 1,842 persons, the majority of whom were males (78.

6%), with an average age of the index offense at 32.7 years. The most prevalent diagnostic subgroup was mild intellectual disability (64.3%), and the average number of past offenses was 3.1, 26.9% having a violent index offense. During a median follow-up period of 4.8 years, 38.7% developed one or more recidivism events, which is an 8.5 incidence rate per 100 person-years. These background facts highlight the susceptibility of this group to recidivism and justify the usefulness of time-to-event modeling in risk forecasting. A longitudinal Cox regression study showed that there are some predictors of recidivism. Out of the static factors, older age at the index offense provided a protective effect, with an extra year of age decreasing the chances of recidivism by 3% (HR = 0.97, 95% CI: 0.96-1.22), and a prior criminal history also led to a significant risk (HR per offence = 1.18, 95% CI: 1.14-1.22). Mildly intellectually disabled individuals were found to be at a 42% increased risk of recidivism relative to other moderate and severely intellectually disabled individuals (HR = 1.42, 95%CI: 1.19-1.69). The influence of time-varying factors also worked: vulnerablement to recidivism was 61 per cent higher when the patient had mental health instability (HR = 1.61, 95% CI: 1.34-1.93), whereas psychological or behavioral treatment and stable housing were protective (HR = 0.66, 95% CI: 0.55-0.79; HR = 0.71, 95% CI: 0.59-0.85, respectively). The detected risk was higher in high supervision intensity (HR = 1.29, 95% CI: 1.08-1.53), which might have been caused by more intense monitoring, as opposed to causation.

The longitudinal model had a high predictive performance with a C-index of 0.73 that was better than a cross-sectional baseline model (C-index = 0.64). Time-specific AUCs were 0.72 to 0.76 (1, 3, and 5 years) with the calibration slope (0.97), indicating that there was minimal bias in the estimation of absolute risk. The added value of using time-varying predictors was also confirmed in comparative analyses, pointing out that dynamic clinical and social predictors add a great deal to the risk stratification in recidivism. Sensitivity analyses also helped substantiate the strength of the results in other outcome definitions, the absence of severe/profound ID cases, and multiply imputed data. On the whole, these results highlight the significance of not only the static but also the dynamic variables in the

prediction of reoffending in people with ID. The modifiable time-varying risk factors (including mental health support, housing stability, and treatment attendance) could be of significant help in reducing recidivism, and the predictive variables, such as age and previous offending, would be a valuable context in risk stratification.

Conclusion

The study is a longitudinal study that examines key predictors of recidivism in 1,842 intellectually disabled offenders (ID). Cases The incidence rate of recidivism among the participants was 8.5\100 at an overall median follow-up of 4.8 years, with 38.7% fretting at least one such occurrence. The presence of such predictors as younger age during the index offense and criminal history was strongly linked with increased risk, with every year of age associating with a 3% lessened hazard (HR = 0.97, 95% CI: 0.96-1.22), and every one previous offense associated with an 18-percent augmented hazard (HR = 1.18, 95% CI: 1.14-1.22). Mild ID individuals were found to be at higher risk of reoffending (42%) than those with moderate/severe ID (HR = 1.42, 95% CI: 1.19-1.69). The recidivism was also affected by other time-varying factors such as mental health instability (HR = 1.61), treatment engagement (HR = 0.66), stable housing (HR = 0.71), and high supervision intensity (HR = 1.29). The longitudinal model had strong predictive validity (C-index= 0.73; time-dependent AUCs = 0.72-0.76) and performed better than a cross-sectional baseline model (C-index = 0.64). Results highlight the relevance of combining both fixed and dynamic variables in the process of risk stratification. The personalized interventions addressing modifiable risk factors, such as mental health support, treatment engagement, housing stability, and the creation of real-time monitoring tools to minimize reoffending and optimize the outcomes of this vulnerable population, should be studied in the future.

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