Comprehensive Psychiatry 149 (2026) 152716

Contents lists available at ScienceDirect

Comprehensive Psychiatry

journal homepage: www.elsevier.com/locate/comppsych

Forensic outcome in schizophrenia: It's the system, not the symptoms

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ARTICLE INFO

Keywords:
Schizophrenia spectrum disorders
Forensic psychiatry
System integration
Social deprivation
Machine learning

ABSTRACT

Background: Schizophrenia spectrum disorders (SSD) are associated with increased risks of criminal behavior, especially if mediated by factors such as substance use. However, it remains unclear whether these factors retain their predictive relevance once broader social and systemic conditions are considered. To date, comparisons between forensic (FPP) and general psychiatric (GPP) SSD patients that systematically test the weight of these factors in complex contexts are scarce. We sought to evaluate whether established clinical risk factors for criminal behavior hold explanatory power once embedded in wider contextual frameworks. Group membership was used as a proxy for such forensic trajectories.

Methods: A retrospective study was conducted using data from 740 patients (370 FPP, 370 GPP) diagnosed with SSD receiving treatment at one institution in Switzerland. Several machine learning algorithms were tested. Gradient Boosting emerged as the most suitable model. Performance metrics such as balanced accuracy, area under the curve (AUC), sensitivity, and specificity were used for model evaluation. Key predictive variables were ranked based on their influence.

Results: Gradient Boosting achieved a balanced accuracy of 77.5% and an AUC of 0.85 (analysis excluding item 'olanzapine-equivalent dose at discharge', which was identified as a potential downstream marker of institutional placement; primary model with all items: 81.6% and 0.88, respectively), outperforming other algorithms in discriminating between the groups. Notable predictors of a forensic-psychiatric course included social isolation across life span and limited mental health care system integration, while psychopathology did not emerge as a relevant predictor.

Conclusion: When comprehensively comparing forensic and general psychiatric SSD patients, social isolation, antipsychotic dosage, and mental health system integration emerge as the primary discriminators, overshadowing well established risk factors. Preventing forensic pathways in SSD requires strengthening social networks and system integration, marking a paradigm shift away from symptom-centered risk models.

1. Introduction

Schizophrenia spectrum disorders (SSD) are associated with an increased likelihood of (violent) criminal behavior, with substance use disorders being a major contributing factor [1,2]. Other potentially modifiable risk factors include non-adherence to psychotherapy and medication, impaired impulse control, and hostility [3]. Positive symptoms, such as delusions and hallucinations, and demographic variables, e. g., male sex, have also been linked to violent behavior [4–6]. While certain factors contributing to criminal behavior among individuals with SSD have been identified, research covering direct comparison of general (GPP) and forensic populations (FPP) is surprisingly scarce. The recent EU-VIORMED study provided invaluable results, highlighting childhood adverse experiences and education as key

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https://doi.org/10.1016/j.comppsych.2026.152716

Available online 15 May 2026

differentiating factors, among others [7]. Importantly, the project focused on interpersonal violence only, although forensic treatments often address non-violent crimes as well [8]. Another study investigating the follow up after discharge found more severe positive and negative symptoms as well as aggression in general psychiatric patients [9]. Psychosis patients who committed homicide after hospital discharge exhibited less adherence to treatment and used more illicit substances, while positive symptoms did not differ between violent and non-violent patients [10]. Other case-control studies highlight the possible role of negative symptoms as a protective factor against the occurrence of aggressive and violent behavior in SSD patients [11]. Individuals with repeated violent or non-violent behavior are often subjected to court-mandated forensic psychiatric treatment [12]. However, patients frequently exhibit warning signs, such as childhood antisocial tendencies, long before engaging in prosecutable offenses. Identifying these patterns is critical for developing preventive measures that could mitigate legal system involvement for SSD patients [13–15].

Criminal behavior in SSD clearly emerges as a multifactorial outcome embedded in complex constellations of clinical, social, and systemic conditions. Rather than analyzing isolated risk factors in a linear fashion, it is therefore essential to examine how different factors interact and which specific configurations truly distinguish patients who enter forensic care from those treated exclusively in general psychiatry. To adequately capture this complexity and the mutual interplay of different influencing factors, supervised machine learning approaches are particularly well suited [16,17]. Previous investigations by our group have further characterized these diverse trajectories in direct comparative analyses between various subgroups of GPP and FPP, identifying specific phenotypes. Notably, a comparison revealed that commonly cited risk factors including comorbid substance use, medication non-compliance, and psychopathology were insufficient to reliably distinguish between violent offender and non-offender SSD patients [18]. However, when a comorbid substance use disorder (SUD) is present, the risk of violence appears to be specifically associated with non-adherence to antipsychotics and insufficient engagement in outpatient treatment, among other factors [19]. We present the first ML study to harness 500+ variables in a large GPP–FPP cohort, testing whether classic clinical risk factors hold up when placed in broader social and systemic frameworks. While previous investigations within this research framework have examined specific domains – such as aggression-related risk factors, suicidality, or isolated social and clinical characteristics – these analyses were typically restricted to predefined subsets of variables or focused research questions. As a result, they provided important but necessarily partial insights into the mechanisms underlying forensic trajectories in SSD. The present study extends this work by integrating a broad range of clinical, social, and systemic variables within a single analytical model. By applying machine learning to a large, comprehensively characterized cohort, it aims to evaluate the relative importance of established risk factors when considered simultaneously within a complex, real-world context. In doing so, this study moves beyond domain-specific analyses and addresses the unresolved question of which factors truly differentiate forensic from non-forensic trajectories when competing influences are taken into account.

2. Methods

The dataset used for both test and validation models consisted of sociodemographic, clinical, and historical variables, which had all been acquired as part of routine clinical documentation and were subsequently extracted from medical records by an experienced psychiatrist through directed qualitative content analysis [20], with a random subset being independently evaluated by another researcher. Inter-rater reliability was calculated with a Cohen's Kappa score of 0.78, indicating substantial agreement [21]. Reporting was in accordance with the current TRIPOD+AI guidelines [22].

The present study is part of a larger research project investigating divergent clinical and developmental trajectories in individuals with SSD. Specifically, this project aimed to systematically compare patients who have come into conflict with the law and entered forensic psychiatric care with those who, despite a comparable diagnosis, remain within general psychiatric treatment settings. Across multiple studies, this framework has been used to examine similarities and differences between these groups with regard to clinical characteristics, social determinants, and patterns of health care utilization, with the overarching goal of identifying factors that contribute to or protect against forensic trajectories.

2.1. Study population and site

The study compared 370 inpatients each from two centers within the University Hospital of Psychiatry Zurich, Switzerland: the Center for Inpatient Forensic Therapy (forensic psychiatric patients, FPP) and the Center for Integrative Psychiatry (general psychiatric patients, GPP).

All patients were male and female adults diagnosed with SSD according to ICD-9 or ICD-10 criteria [23,24]. Forensic treatments were court-mandated under Article 59 of the Swiss Criminal Code or initiated during imprisonment for crisis intervention [25]. Pervasive and specific developmental disorders (ICD-10: F8x) and mental retardation (ICD-10: F7x) were excluded. The inclusion criterion of SSD (F2x) also implicitly excludes organic psychotic disorders (F0x), ensuring a diagnostically homogeneous core population. The treatment period spanned from 1982 to 2016, capturing a wide range of clinical cases. No a priori power calculation was performed due to the exploratory nature of the machine learning analysis. However, the sample size allowed for robust model training and evaluation using cross-validation, and sufficient separation into training and validation datasets (70/30 split). In machine learning, sample size requirements are typically guided by the complexity of the model, the number of features, and the intended generalizability. The final model included a reduced set of 10 key variables after dimensionality reduction, aligning with recommendations in advanced statistics to maintain a ratio of at least 10–20 observations per predictor to reduce overfitting [26,27]. Given this ratio and the sample size of 740, the study is adequately powered for the complexity of the analysis. A post hoc power analysis based on the model's receiver operating characteristics area under the curvve (AUC; see below) indicated that a minimum of 27 participants per group (total $n = 54$) would be required to detect a significant difference with 80% power at $\alpha = 0.05$. The current study included 370 participants in each group ($n = 740$), greatly exceeding this threshold and ensuring sufficient statistical power.

2.2. Statistical and machine learning processes

Descriptive statistics (age, proportions) were evaluated using *t*-test and Chi-Square-Test, respectively; significance level was set to 0.05 [28]. Several structured steps were followed to identify the most discriminative variables using supervised machine learning [29]. All machine learning analysis steps were performed using R version 3.6.3 (The R Project for Statistical Computing, Vienna, Austria) with the MLR package. Confidence intervals for the model performance metrics were calculated using MATLAB R2019a (MATLAB and Statistics Toolbox Release 2012, The MathWorks, Inc., Natick, Massachusetts, USA) with the add-on “computing the posterior balanced accuracy v1.0” [30]. For a comprehensive graphical overview of all steps, please refer to the supplementary material (A).

2.2.1. Preprocessing

Categorical variables were converted into binary codes, while continuous and ordinal variables were left unaltered. Variables with more than 33% missing values were omitted to ensure data quality and model stability. Features with a high proportion of missingness are known to yield unreliable estimates and may introduce bias. Applying a threshold for allowable missingness represents a common strategy in

data preprocessing, balancing the retention of informative variables against the risk of incorporating noise and reducing model robustness. Similar threshold-based approaches have been widely used in applied machine learning studies [31].

The outcome variable – which is necessary for supervised ML – was defined as "not forensic". The dataset was split into a training dataset (70%) and a validation dataset (30%) to reduce the risk of overfitting. This ratio was chosen in accordance with common practice in ML, as empirical studies suggest that allocating approximately 70–80% of the data for training and 20–30% for testing provides a suitable balance between model development and reliable performance estimation [32]. Missing data in the training dataset were imputed using mean imputation for continuous variables and mode imputation for categorical variables [33]. The coefficients for imputation were stored in an "imputationDesc" file for application to the validation dataset. To assess the underlying missingness mechanism, Little's MCAR (missing completely at random) test was conducted for the variables included in the final model [34], indicating that data were not missing completely at random ($p < 0.05$). As a sensitivity analysis, multiple imputation by chained equations (MICE) was applied to the test set of the validation model [35]. Model performance metrics were highly comparable between imputation methods, suggesting robustness of the results with respect to the imputation approach (parameters provided in supplementary material B).

Dimension reduction was conducted using a Random Forest algorithm, a method based on the combination of predictive trees that has been shown to improve accuracy with random feature selection at each node [36,37]. This was done to leverage the model's inherent ability to estimate feature importance, enabling the selection of the most informative variables while discarding redundant or irrelevant features, thereby improving model interpretability and computational efficiency. Variables that did not contribute significantly (at least 5%) to the AUC were removed to lower the risk of overfitting. This threshold-based approach was chosen to ensure that only variables providing a meaningful contribution to predictive performance were retained. In line with established feature selection principles [38], additional predictors were included only as long as they resulted in a relevant improvement in model discrimination. Once the incremental gain in AUC fell below the predefined threshold, further inclusion of variables was considered unlikely to enhance model performance and instead to increase the risk of overfitting and unnecessary model complexity.

2.2.2. Model training

The training set consisted of an even number of GPP and FPP that had been randomly selected from the total population. It was used to evaluate several machine learning algorithms to identify the most effective predictive model. These algorithms included Naïve Bayes, Gradient Boosting, Logistic Regression, Decision Tree, Random Forest, k-Nearest Neighbors, and Support Vector Machines. The evaluation criteria included sensitivity, specificity, balanced accuracy (arithmetic mean of sensitivity and specificity), positive predictive value (PPV), negative predictive value (NPV), and AUC for receiver operating characteristics [39]. A definition of all these parameters can be found in the supplementary material B. Five-fold cross-validation, involving repeated training and evaluation of the model on the different subsets of the data to ensure stable and generalizable performance, was employed after the selection of the best-performing algorithm to further reduce the risk of overfitting [40]. During this step, the training data were partitioned into five equally sized subsets. In each iteration, one subset was used for model training, including all previous steps (imputation, filtering, and the model building process), while the remaining four subsets served to assess the model's performance. This rigorous split of data used for validation purposes from model development also minimizes the bias regarding the expected generalization performance [39]. The model with the highest AUC was chosen for validation purposes on the test data since the AUC represents a threshold-independent measure of overall discriminative performance, quantifying a classifier's ability to distinguish between classes across all possible decision boundaries – an advantage over single-threshold metrics such as sensitivity or specificity alone, which reflect performance at only one operating point [39,41]. As the seven algorithms produced varying sensitivity/specificity trade-offs, the AUC provided the most objective and comprehensive basis for model selection.

2.2.3. Model validation

The validation dataset was prepared using the same imputation coefficients applied to the training dataset, as stored in the "imputationDesc" file. The Gradient Boosting model was applied to the validation dataset to assess its performance. Variable importance was ranked based on relative influence in the model. Given the pronounced impact of the Olanzapine-equivalent dose at discharge (item R9e), an additional validation run was conducted excluding this variable. The model structure was maintained while assessing its robustness without item R9e.

For further considerations regarding class imbalance and fairness as well as a disclaimer on model specification, please refer to the supplementary (B).

3. Results

The study sample consisted predominantly of male patients in their mid-thirties. A larger proportion of FPP had a history of migration compared to GPP, based on their country of birth. Both groups displayed a similar rate of single marital status and schizophrenia as the primary diagnosis. However, comorbid personality and substance use disorders were more prevalent in the FPP group (see Table 1). Regarding the nature of offenses, 294 FPP (79.7%) had committed a violent index offense, while 75 (20.3%) had committed a non-violent index offense.

Gradient Boosting emerged as the most effective algorithm for distinguishing between FPP and GPP, achieving a balanced accuracy of 83.5% and an AUC of 0.92 (Table 2). This performance made it the model of choice for validation. During the validation phase, the model

Table 1
Basic data.

Variable description	FPP		GPP		Statistical significance (*p*-value)
	n/N (%)	Mean (SD)	n/N (%)	Mean (SD)	
Age at admission (years)		34.2 (10.2)		36.2 (12.2)	**0.015**
Sex: male*	339/370 (91.6)		339/370 (91.6)		1
Country of birth: Switzerland	167/370 (45.1)		245/369 (66.4)		**<0.001**
Marital status: single	297/364 (81.6)		284/366 (77.6)		0.199
Diagnosis: Schizophrenia	294/370 (79.5)		291/369 (78.9)		0.857
Comorbid Substance Use Disorder	269/369 (72.9)		184/330 (55.8)		**<0.001**
Comorbid Personality Disorder	47/368 (12.8)		27/281 (9.6)		0.216
Comorbid ADHD	24/290 (8.3)		24/208 (11.5)		0.233

* According to patients' files. Note. n = sample size with characteristic. N = total sample size. SD = Standard deviation. Bold font = statistically significant (level 0.05).

Table 2
Machine learning models and performance in nested cross-validation.

Performance parameters of each applied algorithm during model training						
	AUC	Balanced accuracy (%)	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)
Logistic Regression	0.90	83.2	83.2	83.3	82.5	83.9
Tree	0.86	81.8	82.1	81.5	80.4	82.7
Random Forest	0.91	82.3	83.0	81.6	81.1	83.7
Gradient Boosting	0.92	83.5	83.4	83.7	82.8	84.2
KNN	0.88	80.4	82.8	78.0	78.2	82.4
SVM	0.90	82.9	79.6	86.3	84.4	82.0
Naive Bayes	0.89	82.9	85.3	80.5	80.5	85.6

Final model performance parameters						
	AUC (95% CI)	**Balanced accuracy** (%, 95% CI)	**Sensitivity** (%, 95% CI)	**Specificity** (%, 95% CI)	**PPV** (%, 95% CI)	**NPV** (%, 95% CI)
Gradient Boosting with item R9e	0.88 (0.83–0.93)	81.6 (75.7–85.9)	80.7 (72.2–87.1)	82.5 (73.5–89.0)	84.2 (75.9–90.1)	78.7 (69.6–85.8)
Gradient Boosting without item R9e	0.85 (0.80–0.90)	77.5 (71.4–82.3)	77.3 (68.5–84.3)	77.7 (68.2–85.0)	80 (71.3–86.7)	74.8 (65.3–82.4)

Note. GPP were defined as positive class. AUC = area under the curve; PPV = positive predictive value; NPV = negative predictive value; KNN = k-nearest neighbors; SVM = support vector machines, CI = confidence interval. Item R9e refers to the Olanzapine-equivalent upon discharge from the referenced hospitalization.

was tested both with and without the inclusion of the Olanzapine-equivalent dose (item R9e). When item R9e was included, the model exhibited slightly lower balanced accuracy and AUC compared to the training phase, but maintained narrow 95% confidence intervals, confirming its reliability. When item R9e was excluded, the model's predictive power decreased slightly, with a balanced accuracy of 77.5% and an AUC of 0.85, reflecting the strong influence of item R9e on model performance.

A total of ten variables were identified as influential predictors in the model (Table 3). Forensic patients were prescribed significantly higher Olanzapine-equivalent doses at discharge compared to general patients (22.1 mg vs. 19.3 mg). Social isolation was also more prevalent in FPP, occurring during childhood, before hospitalization, and upon discharge. FPP were more likely to lack compulsory school education and to have less family support, as reflected in reduced help-seeking behavior by relatives. In contrast, GPP had more frequent inpatient and outpatient treatments before their current hospitalization, demonstrated better adherence to prior antipsychotic treatment, and were prescribed a wider variety of medications.

Variable importance rankings revealed that item R9e was the most influential variable, contributing approximately 50% of the model's predictive power (Fig. 1a). The remaining nine variables collectively accounted for the other 50%. When item R9e was excluded, item PH27b became the most influential variable, and item PH19a the least. Without item R9e, the importance of the remaining variables ranged from approximately 3% to 15% (Fig. 1b).

Table 3
Absolut and relative distribution of relevant predictor variables (including item R9e).

Variable code	Variable description	FPP n/N (%)	GPP n/N (%)
		89/342	18/320
SD7a	No compulsory school education	**(26.0)**	(5.6)
		142/278	32/143
CJ1	Social marginalization in childhood	**(51.1)**	(22.4)
	Outpatient psychiatric treatment(s)	179/340	**278/329**
PH18a	before current hospitalization	(52.6)	**(84.5)**
	Inpatient psychiatric treatment(s) before	259/351	**345/366**
PH19a	current hospitalization	(73.8)	**(94.3)**
		224/370	**330/353**
PH23a	Any antipsychotic medication in the past	(60.5)	**(93.5)**
	Medication compliance (in psychiatric	23/204	**167/306**
PH23p	history)	(11.3)	**(54.6)**
	Help-seeking behavior by relatives	155/321	**192/263**
PH27b	before current hospitalization	(48.3)	**(73.0)**
	Social isolation before current	**174/363**	69/331
S9i	hospitalization	**(47.9)**	(20.8)
	Olanzapine-equivalent dose at discharge	**22.1**	19.3
R9e	(in milligram, standard deviation)	**(12.3)**	(14.2)
		140/369	76/325
R25a	No social contacts at discharge	**(37.9)**	(23.4)

Note: n = sample size with characteristic. N = total sample size.

4. Discussion

Our findings indicate that forensic pathways in schizophrenia are shaped highly, if not primarily by social and systemic embedding, rather than by psychopathology: For FPP, social marginalization often begins in childhood and persists into adulthood, highlighting its significant role in shaping pathways to crime as possible outcome of SSD. FPP were also less likely to be engaged in the mental health care system prior to their current hospitalization than their comparison group of GPP (in- and outpatient treatments, better adherence). Interestingly, the study detected no significant differences in symptomatology and comorbidity between the two groups, as indicated by the fact that no variables linked to psychopathology emerged in the discriminative model.

4.1. Locked out of systems, not locked in by symptoms: relevant predictor items

Differences between forensic and general patients arose from markers of social isolation, educational disadvantage, and weak system engagement.

The most influential single variable in the predictive model, however, was olanzapine-equivalent dose at discharge (item R9e) – a finding that requires careful interpretation. Since item R9e reflects the olanzapine-equivalent dose at discharge from the current hospitalization, it may represent a downstream consequence of institutional placement rather than an antecedent risk factor for forensic trajectories, and its interpretation as an explanatory variable therefore warrants caution. A sensitivity analysis excluding olanzapine-equivalent dose at discharge confirmed that the model remained stable, with all performance parameters falling within the 95% confidence intervals of the primary analysis. Statistically, the difference in Olanzapine dosages between FPP and GPP was significant. However, from a clinical perspective, the absolute difference was marginal at 2.8 mg, with both groups receiving doses close to the licensed maximum according to regulatory approvals. In general, psychopharmacological treatment strategies in forensic psychiatry are often informed by a scarcity of robust research [42]. Existing data remain inconsistent, with some

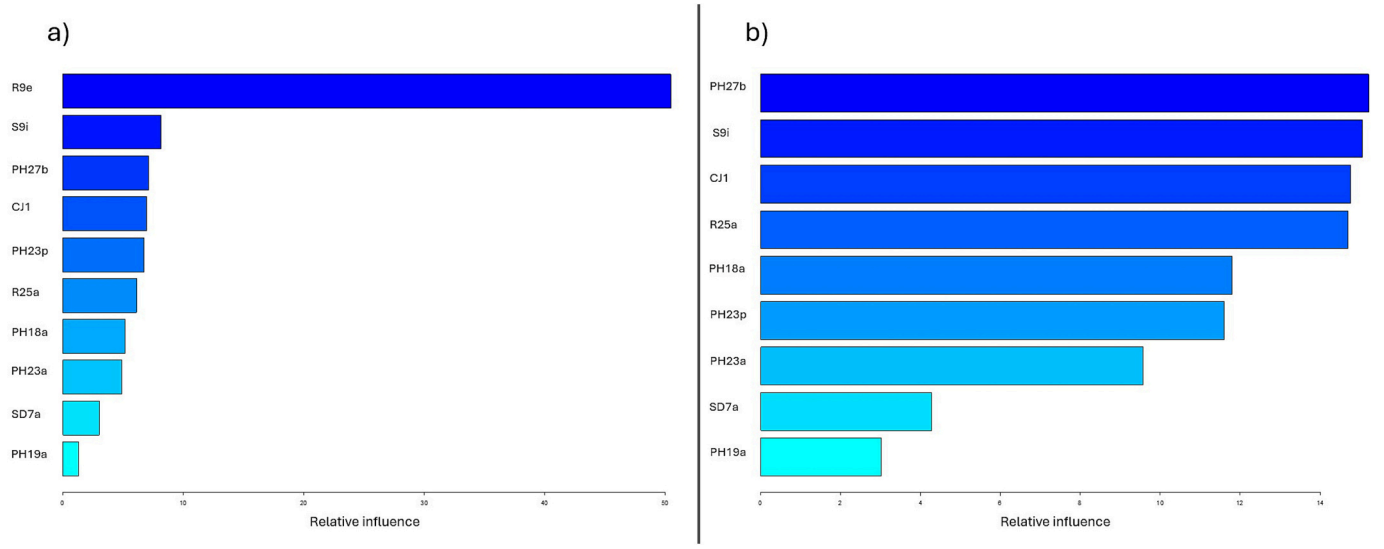

Fig. 1. Variable importance (final gradient boosting model), (a) with item R9e, (b) without item R9e. Please refer to Table 3 for definitions of variable codes.

studies reporting contradictory conclusions. For instance, a similar comparative study with fewer participants found lower prescribed antipsychotic doses in FPP [43]. Conversely, there appears to be a broader trend of high-dosage pharmacotherapy in forensic care [44]. These differences might be attributable to the unique characteristics of health care centers or variations in legal systems governing forensic care.

Social isolation and lack of compulsory school education emerged as important factors distinguishing both groups. FPP were found to have shorter durations of formal education compared to GPP. This finding aligns with existing evidence that greater educational attainment reduces the risk of interpersonal violence [7]. A follow-up study examining patients post-discharge similarly reported lower rates of high school completion among FPP, further corroborating the association between educational deficits and increased risk of offending [9]. Social isolation upon discharge was also more frequent among FPP, potentially attributable to a phenomenon of double stigmatization: FPP face not only the stigma associated with mental illness but also that stemming from their criminal actions [45]. Involvement of relatives is crucial in mitigating this isolation, and clinicians should provide early and proactive support to strengthen patients' social networks, ideally before any criminal behavior manifests. Isolation prior to the index offense in FPP may also be linked to impaired social cognitive functions. These deficits, including difficulties in face recognition and mentalization, are essential for forming and maintaining social bonds [46]. Social marginalization, characterized by adverse childhood experiences, poverty, and social exclusion, compounds these challenges. Individuals with a combination of these factors face a higher lifetime risk of committing crimes and experiencing psychiatric disorders [47]. Therapeutic efforts often come long after these adverse experiences, making it challenging for individuals to effectively cope with their consequences. Our findings reinforce existing evidence that societal disparities must be addressed to mitigate these risks [48]. Structural interventions targeting social inequalities, particularly at an early stage, are essential to counterbalance the lifelong impacts of marginalization [49,50]. Involvement with the mental health care system plays a critical role in mitigating the risk of criminal behavior among individuals with SSD. Insufficient access to or engagement with mental health care has been established as a significant correlate of criminal behavior, a negative outcome frequently observed in the course of SSD. Effective pharmacotherapy has the potential to reduce rates of violent behavior, underscoring the importance of adequate treatment during all stages of the illness [51].

4.2. When usual suspects fail to explain: items not included in the discriminative model

The absence of certain expected predictors in the ML model is itself a key finding: Traditional risk markers such as psychopathology, comorbid substance use, and personality disorder showed limited discriminative power once broader systemic and social factors were considered. This seems contrasting to existing literature, with some data showing the association of positive symptoms and violence [3], and other even reporting more positive symptoms in GPP [7]. Consistent with previous studies, a higher proportion of FPP were found to have SUD. This finding underscores the importance of addressing SUD in therapeutic interventions for FPP [1–3,52].

Although SUD, personality and other comorbid psychiatric disorders were not significant predictors in our model, they might still play a relevant role, as highlighted by previous research [1,2,7]. There are several hypotheses regarding these well-known risk factors for criminal behavior in SSD not emerging as defining discriminative factors. First, this may reflect potential compensatory effects of adequate social support and effective integration into the mental health care system, which could mitigate the impact of SUD and personality disorder on forensic outcomes. An additional aspect that may contribute to the limited discriminative role of particularly SUD in the present model concerns the variability and potential bias in their clinical assessment. The identification and documentation of SUD in routine clinical records may be influenced by differences in diagnostic thresholds, clinician attitudes, and contextual priorities. In the diagnostic assessment and treatment of offenders with SSD, particularly in cases characterized by high illness severity, SUD may be recorded as secondary diagnoses and considered subordinate within the broader offense-related psychopathology. Under such conditions, clinical attention is likely to be directed primarily toward the underlying psychotic disorder, potentially leading to an underrepresentation of less severe forms of substance use – such as harmful use below the threshold of addiction – in routine clinical documentation. Substance use may at times also be conceptualized as a secondary behavioral manifestation rather than a distinct diagnostic entity, potentially resulting in inconsistent recording practices. Retrospective substance use problems, although clinically relevant for long-term outcomes such as relapse and recidivism, may therefore be insufficiently captured in datasets derived from routine documentation. Taken together, these considerations suggest that the apparent lack of discriminative power of SUD should be interpreted with caution and may, at least in part, reflect limitations in measurement rather than a

true absence of effect. At the same time, our findings raise the possibility that, within sufficiently supportive and well-integrated care contexts, the impact of SUD on forensic trajectories may be attenuated, highlighting the potential of social and systemic factors to buffer established clinical risks.

Secondly, descriptive statistics revealed a significantly higher proportion of FPP with a personal history of migration. This finding aligns with research indicating that migration may increase the burden of disease, impair communication due to language or cultural barriers, and create systemic barriers to accessing mental health care [53–55]. Social isolation is also more common in migrants, as family members often remain in their countries of origin, compounding challenges related to language and cultural differences. These factors may contribute to the observed lower rates of prior treatment among FPP with migration histories, reflecting known trends of under-utilization of mental health care in European countries. Barriers such as language difficulties, low awareness of resources, and cultural stigma likely play a role [56]. Yet no item directly related to a migration experience turned out to be of relevance in the discriminative model.

The predominance of system integration factors over traditional clinical risk markers raises important questions about underlying mechanisms. Social isolation may reduce opportunities for corrective feedback and reality checking, potentially amplifying the impact of psychotic symptoms on behavioral outcomes [57].

Inadequate mental health care engagement could result in poor medication adherence and insufficient crisis intervention during symptom exacerbations, which in turn increase the risk for violent acts [51]. Additionally, the absence of supportive social networks may create a state where patients become increasingly antagonistic toward their environment due to unaddressed distress and lack of interpersonal bonding. From a developmental perspective, early social marginalization may represent a form of childhood deprivation that counteracts vital developmental periods for emotional regulation, empathy formation, and prosocial behavior acquisition [58,59]. Such early adversity could create lasting deficits in interpersonal functioning that persist into adulthood, making individuals more vulnerable to antisocial outcomes when combined with the cognitive and emotional challenges of SSD [60]. These mechanisms suggest that criminal behavior in SSD may emerge less from illness severity per se, but rather from the interaction between symptoms and inadequate social and clinical support systems, potentially compounded by early developmental disruptions. While the present findings originate from a single institution operating within the specific legal framework of the Swiss Criminal Code, the core results are potentially transferable across different forensic psychiatric systems. The primary discriminators identified – limited social and system integration – are not institutional artefacts but reflect structural determinants of social marginalization that operate independently of local legal frameworks. Social exclusion and disengagement from mental health services have been identified as severe issues across multiple national contexts and health care systems [61,62]. Precisely because the dominant predictors in our model are social and systemic rather than clinically or legally specific, they may represent a more robust signal than findings centered on psychopathology or pharmacotherapy, which are more susceptible to institutional variation. This does not preclude that the relative weighting of individual predictors may differ across systems – a question that multi-center replication studies would be well-suited to address.

Also, it should be acknowledged that the outcome variable – forensic vs. general psychiatric treatment – reflects not only clinical but also judicial processes. Assignment to forensic care is shaped by legal interpretations of criminal responsibility and the structure of the local forensic mental health system, introducing a layer of complexity that extends beyond purely clinical prediction. This perspective aligns with the criminalization hypothesis, which hypothesizes that insufficient community mental health engagement is a key driver of the disproportionate entry of individuals with severe mental disorders into the criminal justice system [63]. Importantly, this does not undermine our core findings: if social marginalization and system disengagement influence both clinical trajectories and the contexts in which offenses occur and are adjudicated, their prominence as discriminators is theoretically consistent. Awareness of cognitive and contextual biases in forensic risk assessment further underscores this complexity [64].

4.3. Strengths and limitations

This study's retrospective, single-center design, with data drawn from one country, limits transferability to other care systems, particularly since forensic psychiatric pathways are shaped by local legal structures as well as by regional service organization and institutional practices. Again, multi-center and international replication studies remain necessary to empirically test this proposition. The focus on inpatients, with over 90% of participants being men, reduces the generalizability to less severe cases requiring only outpatient care, as well as to female populations. At the same time, the imbalanced sex distribution reflects the reality of penitentiary populations.

The observation period spanning 1982 to 2016 encompasses considerable temporal heterogeneity, including a transition from ICD-9 to ICD-10 diagnostic criteria, evolving treatment standards, and changes in forensic psychiatric practice. Changes in diagnostic systems and thresholds over time may have influenced the classification of psychiatric disorders, while advances in pharmacological and psychosocial treatment may have altered clinical trajectories and outcomes. In addition, evolving forensic assessment practices and legal frameworks may have affected the evaluation and documentation of risk-related variables. These temporal shifts may contribute to variability in the recorded data. However, as the majority of cases were recruited from the year 2000 onwards, the impact of earlier variability is likely limited. The extended inclusion period reflects a deliberate trade-off between minimizing temporal heterogeneity and ensuring a sufficiently large and statistically meaningful sample size. Future studies incorporating explicit epoch-stratified sensitivity analyses would be well-positioned to further examine the potential impact of such historical heterogeneity.

ML methods perform better with larger datasets, and the relatively limited sample size increases the risk of overfitting. Future studies should aim to replicate these findings using data from multiple centers and countries to enhance the robustness and generalizability of the results. Additionally, ethical considerations surrounding the application of ML in sensitive fields like forensic psychiatry must be addressed. Recent developments promote the use of Explainable AI over traditional AI approaches to improve transparency and understanding of ML outputs, particularly in high-stakes fields like forensic psychiatry [65]. This is critical for preventing stigmatization, as patients identified as “high risk” due to social isolation or other factors may face additional challenges in reintegration [66]. While some of the most influential predictors (e.g., low education, limited family support, social marginalization) may reflect structural inequalities, they also emerged as statistically relevant. This highlights the complex interplay between clinical, social, and systemic factors in forensic outcomes. Future studies may consider formal fairness auditing or mitigation strategies. In addition, potential bias related to missing data should be considered, as the MCAR (missing completely at random) assumption was not met and systematic patterns in missingness cannot be excluded. However, sensitivity analyses using multiple imputation yielded comparable results, supporting the robustness of the findings.

Despite methodological and contextual limitations, the study demonstrates the added value of machine learning for uncovering system-level drivers of forensic outcomes and has notable strengths: With a sample size of 740 patients, it is nearly twice as large as the EU-VIORMED project, which itself marked a significant milestone in the comparison of FPP and GPP [7]. The inclusion of environmental and social variables, rather than focusing solely on psychopathology and criminal history, is another key strength. Previous authors have

highlighted the importance of incorporating these contextual factors when addressing ethical concerns in the application of AI in forensic psychiatry [67]. ML allowed for the analysis of variable interplay rather than simple linear relationships, addressing the multifaceted nature of forensic outcomes [16]. The robust AUC values, even after excluding item R9e (olanzapine-equivalent dose at discharge), further validate the model's reliability [68].

4.4. Conclusion

FPP and GPP with SSD share many similarities, particularly regarding psychopathology. However, key differences were observed in social inclusion across the course of life and regarding involvement with the mental health care system prior to the index hospitalization. These findings might represent a paradigm shift in understanding risk factors for criminal behavior in SSD. While previous research comparing individuals with SSD to the general population has identified psychopathology and substance use as key risk factors, direct comprehensive comparisons between forensic and non-forensic SSD patients have been scarce. Our ML analysis of this specific comparison reveals that system integration - featuring both social connectedness and mental health care involvement - emerges as the predominant differentiating factor, overshadowing traditional clinical risk markers.

These insights have direct implications for clinical practice and policy: early interventions should prioritize strengthening social networks and ensuring comprehensive mental health care engagement rather than focusing exclusively on symptom management or substance use treatment. Forensic mental health services could benefit from adopting integrative psychiatric approaches that emphasize community integration, family involvement, and peer support - strategies already getting more and more relevant in general psychiatry. Future research should focus on longitudinal studies to explore causal pathways, cross-cultural analyses to assess differences in legal and healthcare systems, and the integration of Explainable AI to enhance transparency and ethical application of machine learning in forensic psychiatry.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.comppsych.2026.152716.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used Claude Sonnet 4 (Anthropic, 2025) in order to improve structure and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Lena Machetanz: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Andreas B. Hofmann:** Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Marc Dörner:** Writing – review & editing, Validation. **Erich Seifritz:** Writing – review & editing, Validation, Supervision. **Philipp Homan:** Writing – review & editing, Supervision, Project administration. **Johannes Kirchebner:** Writing – original draft, Validation, Supervision, Project administration, Formal analysis, Data curation, Conceptualization.

Ethics approval and consent to participate

The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2013. All procedures involving human subjects/patients were approved by the Ethics Committee of Zurich under reference number KEK-ZH-NR 2014–0480 (approved on May 19, 2015). Patient consent was waived due to the retrospective design, for which formal consent is not necessarily required in the Canton of Zurich.

Funding

This research received no specific grant from any funding agency, commercial or not-for-profit sectors.

Declaration of competing interest

Erich Seifritz reports a relationship with Angelini, Boehringer Ingelheim, Lundbeck, Mepha, OM Pharma, Otsuka, Recordati, Roche Pharma, Sandoz, Schwabe Pharma, Janssen Cilag, Servier, Sunovion, Takeda and Vifor that includes: consulting or advisory, funding grants, and speaking and lecture fees. Philipp Homan reports a relationship with Novartis, Lundbeck, Mepha, Janssen, OM Pharma, Boehringer Ingelheim and Neurolite that includes: consulting or advisory and funding grants. The other authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

None.

Data availability

The datasets supporting this article are available from the corresponding author upon reasonable request. A detailed list of all our variables (including definitions and references) is available under the following link: https://www.researchgate.net/publication/363044110_Coding_protocol_Pathways_into_delinquency_in_offenders_suffering_from_schizophrenia_spectrum_disorders.

The machine learning code used for this study is available on Zenodo under the following link: https://doi.org/10.5281/zenodo.19689364.

References

[1] Fazel S, Langstrom N, Hjern A, Grann M, Lichtenstein P. Schizophrenia, substance abuse, and violent crime. JAMA 2009;301(19):2016–23. https://doi.org/10.1001/jama.2009.675.
[2] Fazel S, Gulati G, Linsell L, Geddes JR, Grann M. Schizophrenia and violence: systematic review and meta-analysis. PLoS Med 2009;6(8):e1000120. https://doi.org/10.1371/journal.pmed.1000120.
[3] Witt K, van Dorn R, Fazel S. Risk factors for violence in psychosis: systematic review and meta-regression analysis of 110 studies. PloS One 2013;8(2):e55942. https://doi.org/10.1371/journal.pone.0055942.
[4] Ciubara A, Cartas N, Burlea LS, Chirita R, Ciubara BA, Untu I, et al. The relationship between schizophrenia and criminality. Eur Psychiatry 2015;30:763. https://doi.org/10.1016/S0924-9338(15)30603-9.
[5] Whiting D, Gulati G, Geddes JR, Fazel S. Association of schizophrenia spectrum disorders and violence perpetration in adults and adolescents from 15 countries: a systematic review and meta-analysis. JAMA Psychiatry 2022;79(2):120–32. https://doi.org/10.1001/jamapsychiatry.2021.3721.
[6] Lin R, Li Q, Liu Z, Zhong S, Huang Y, Cao H, et al. Risk factors for violent crime in patients with schizophrenia: a retrospective study. PeerJ 2024;12:e18014. https://doi.org/10.7717/peerj.18014.
[7] de Girolamo G, Iozzino L, Ferrari C, Gosek P, Heitzman J, Salize HJ, et al. A multinational case-control study comparing forensic and non-forensic patients with schizophrenia spectrum disorders: the EU-VIORMED project. Psychol Med 2023;53(5):1814–24. https://doi.org/10.1017/S0033291721003433.
[8] Habermeyer E, Wolff R, Gillner M, Strohm R, Kutscher S. Patients with psychotic disorders in forensic psychiatric hospitals: are there consequences for general psychiatry? Nervenarzt 2010;81(9):1117–24. https://doi.org/10.1007/s00115-009-2913-z.
[9] Hodgins S, Müller-Isberner R, Freese R, Tiihonen J, Repo-Tiihonen E, Eronen M, et al. A comparison of general adult and forensic patients with schizophrenia living in the community. Int J Forensic Ment Health 2007;6(1):63–75. https://doi.org/10.1080/14999013.2007.10471250.
[10] Fazel S, Buxrud P, Ruchkin V, Grann M. Homicide in discharged patients with schizophrenia and other psychoses: a national case-control study. Schizophr Res 2010;123(2–3):263–9. https://doi.org/10.1016/j.schres.2010.08.019.
[11] Bulgari V, Iozzino L, Ferrari C, Picchioni M, Candini V, De Francesco A, et al. Clinical and neuropsychological features of violence in schizophrenia: a

prospective cohort study. Schizophr Res 2017;181:124–30. https://doi.org/10.1016/j.schres.2016.10.016.
[12] Beis P, Graf M, Hachtel H. Impact of legal traditions on forensic mental health treatment worldwide. Front Psych 2022;13:876619. https://doi.org/10.3389/fpsyt.2022.876619.
[13] Hodgins S, Piatosa MJ, Schiffer B. Violence among people with schizophrenia: phenotypes and neurobiology. Curr Top Behav Neurosci 2014;17:329–68. https://doi.org/10.1007/7854_2013_259.
[14] Lau S, Gunther MP, Kling S, Kirchebner J. Latent class analysis identified phenotypes in individuals with schizophrenia spectrum disorder who engage in aggressive behaviour towards others. Eur Psychiatry 2019;60:86–96. https://doi.org/10.1016/j.eurpsy.2019.05.005.
[15] Hodgins S, Klein S. New clinically relevant findings about violence by people with schizophrenia. Can J Psychiatry 2017;62(2):86–93. https://doi.org/10.1177/0706743716648300.
[16] Rajula HSR, Verlato G, Manchia M, Antonucci N, Fanos V. Comparison of conventional statistical methods with machine learning in medicine: diagnosis, drug development, and treatment. Medicina (Kaunas) 2020;56(9). https://doi.org/10.3390/medicina56090455.
[17] Zhou Z, Wu TC, Wang B, Wang H, Tu XM, Feng C. Machine learning methods in psychiatry: a brief introduction. Gen Psychiatr 2020;33(1):e100171. https://doi.org/10.1136/gpsych-2019-100171.
[18] Kirchebner J, Lau S, Machetanz L. Offenders and non-offenders with schizophrenia spectrum disorders: do they really differ in known risk factors for aggression? Front Psych 2023;14:1145644. https://doi.org/10.3389/fpsyt.2023.1145644.
[19] Bender EM, Machetanz L, von Kanel R, Euler S, Kirchebner J, Gunther MP. When do drugs trigger criminal behavior? A machine learning analysis of offenders and non-offenders with schizophrenia and comorbid substance use disorder. Front Psych 2024;15:1356843. https://doi.org/10.3389/fpsyt.2024.1356843.
[20] Hsieh HF, Shannon SE. Three approaches to qualitative content analysis. Qual Health Res 2005;15(9):1277–88. https://doi.org/10.1177/1049732305276687.
[21] Brennan PF, Hays BJ. The kappa statistic for establishing interrater reliability in the secondary analysis of qualitative clinical data. Res Nurs Health 1992;15(2):153–8. https://doi.org/10.1002/nur.4770150210.
[22] Collins GS, Moons KGM, Dhiman P, Riley RD, Beam AL, Van Calster B, et al. TRIPOD+AI statement: updated guidance for reporting clinical prediction models that use regression or machine learning methods. BMJ 2024;385:e078378. https://doi.org/10.1136/bmj-2023-078378.
[23] WHO. The ICD-10 classification of mental and behavioural disorders: clinical descriptions and diagnostic guidelines. Geneva: World Health Organization, WHO; 1992.
[24] Slee VN. The international classification of diseases: ninth revision (ICD-9). American College of Physicians; 1978. p. 424–6.
[25] Fedlex. Swiss criminal code 2023. updated 09/01/2023. Available from: https://www.fedlex.admin.ch/eli/cc/54/757_781_799/en; 2023.
[26] Hastie T, Tibshirani R, Friedman J. Model assessment and selection. In: The Elements of Statistical Learning: Data Mining, Inference, and Prediction. New York, NY: Springer New York; 2009. p. 219–59.
[27] Peduzzi P, Concato J, Kemper E, Holford TR, Feinstein AR. A simulation study of the number of events per variable in logistic regression analysis. J Clin Epidemiol 1996;49(12):1373–9. https://doi.org/10.1016/s0895-4356(96)00236-3.
[28] Altman DG. Practical statistics for medical research. Taylor & Francis; 1990.
[29] Osisanwo F, Akinsola J, Awodele O, Hinmikaiye J, Olakanmi O, Akinjobi J. Supervised machine learning algorithms: classification and comparison. Int J Comput Trends Technol 2017;48(3):128–38.
[30] Brodersen KH, Ong CS, Stephan KE, Buhmann JM, editors. The balanced accuracy and its posterior distribution. 2010 20th international conference on pattern recognition. IEEE; 2010.
[31] Joel LO, Doorsamy W, Paul BS. On the performance of imputation techniques for missing values on healthcare datasets. arXiv preprint; 2024. arXiv:240314687.
[32] Gholamy A, Kreinovich V, Kosheleva O, editors. Why 70/30 or 80/20 relation between training and testing sets: a pedagogical explanation; 2018.
[33] Thomas T, Rajabi E. A systematic review of machine learning-based missing value imputation techniques. Data Technol Appl 2021;55(4):558–85. https://doi.org/10.1108/DTA-12-2020-0298.
[34] Li C. Little's test of missing completely at random. Stata J 2013;13(4):795–809. https://doi.org/10.1177/1536867x1301300407.
[35] Azur MJ, Stuart EA, Frangakis C, Leaf PJ. Multiple imputation by chained equations: what is it and how does it work? Int J Methods Psychiatr Res 2011;20(1):40–9. https://doi.org/10.1002/mpr.329.
[36] Archer KJ, Kimes RV. Empirical characterization of random forest variable importance measures. Comput Stat Data Anal 2008;52(4):2249–60. https://doi.org/10.1016/j.csda.2007.08.015.
[37] Gadekallu T, Reddy P, Lakshman K, Kaluri R, Rajput D, Srivastava G, et al. Analysis of dimensionality reduction techniques on big data. IEEE Access 2020:1. https://doi.org/10.1109/ACCESS.2020.2980942.
[38] Mohtasham F, Pourhoseingholi M, Hashemi Nazari SS, Kavousi K, Zali MR. Comparative analysis of feature selection techniques for COVID-19 dataset. Sci Rep 2024;14(1):18627. https://doi.org/10.1038/s41598-024-69209-6.
[39] Varoquaux G, Colliot O. Evaluating machine learning models and their diagnostic value. In: Colliot O, editor. Machine learning for brain disorders. New York, NY: Springer US; 2023. p. 601–30.
[40] Browne MW. Cross-validation methods. J Math Psychol 2000;44(1):108–32. https://doi.org/10.1006/jmps.1999.1279.
[41] Campbell G. Advances in statistical methodology for the evaluation of diagnostic and laboratory tests. Stat Med 1994;13(5–7):499–508. https://doi.org/10.1002/sim.4780130513.
[42] Howner K, Andiné P, Engberg G, Ekström EH, Lindström E, Nilsson M, et al. Pharmacological treatment in forensic psychiatry-a systematic review. Front Psych 2019;10:963. https://doi.org/10.3389/fpsyt.2019.00963.
[43] Vasic N, Segmiller F, Rees F, Jäger M, Becker T, Ormanns N, et al. Psychopharmacologic treatment of in-patients with schizophrenia: comparing forensic and general psychiatry. J Forensic Psychiatry Psychol 2018;29(1):1–15. https://doi.org/10.1080/14789949.2017.1332773.
[44] Margetic B, Aukst Margetic B, Ivanec D, Zarkovic Palijan T. What leads to high antipsychotic dosing in forensic patients with schizophrenia? CNS Spectr 2017;22(6):435–8. https://doi.org/10.1017/S1092852916000675.
[45] Markham S. Stigmatization and marginalization of forensic psychiatric patients. Illn Crisis Loss 2025;33(3):10541373241268095. https://doi.org/10.1177/10541373241268095.
[46] Green MF, Horan WP, Lee J. Social cognition in schizophrenia. Nat Rev Neurosci 2015;16(10):620–31. https://doi.org/10.1038/nrn4005.
[47] Tomlin J, Völlm B. Diversity and marginalisation in forensic mental health carexxi. New York, NY, US: Routledge; 2023. p. 199.
[48] Selten J-P, van der Ven E, Rutten BPF, Cantor-Graae E. The social defeat hypothesis of schizophrenia: an update. Schizophr Bull 2013;39(6):1180–6. https://doi.org/10.1093/schbul/sbt134.
[49] Kirkbride JB, Anglin DM, Colman I, Dykxhoorn J, Jones PB, Patalay P, et al. The social determinants of mental health and disorder: evidence, prevention and recommendations. World Psychiatry 2024;23(1):58–90. https://doi.org/10.1002/wps.21160.
[50] Cook BL, Rastegar J, Patel N. Social risk factors and racial and ethnic disparities in health care resource utilization among medicare advantage beneficiaries with psychiatric disorders. Med Care Res Rev 2024;81(3):209–22. https://doi.org/10.1177/10775587231222583.
[51] Fazel S, Zetterqvist J, Larsson H, Langstrom N, Lichtenstein P. Antipsychotics, mood stabilisers, and risk of violent crime. Lancet 2014;384(9949):1206–14. https://doi.org/10.1016/S0140-6736(14)60379-2.
[52] Patterson A, Sonnweber M, Lau S, Gunther MP, Seifritz E, Kirchebner J. Schizophrenia and substance use disorder: characteristics of coexisting issues in a forensic setting. Drug Alcohol Depend 2021;226:108850. https://doi.org/10.1016/j.drugalcdep.2021.108850.
[53] Rousseau C, Frounfelker RL. Mental health needs and services for migrants: an overview for primary care providers. J Travel Med 2019;26(2). https://doi.org/10.1093/jtm/tay150.
[54] Khan B, Simpson AIF. Another call to action for integrating culture into forensic therapeutics. J Am Acad Psychiatry Law 2022;50(3):434–9. https://doi.org/10.29158/JAAPL.210139-21.
[55] Forray AI, Oltean O, Hanft-Robert S, Madzamba R, Liem A, Schouten B, et al. Uncovering multi-level mental healthcare barriers for migrants: a qualitative analysis across China, Germany, Netherlands, Romania, and South Africa. BMC Public Health 2024;24(1):1593. https://doi.org/10.1186/s12889-024-19046-z.
[56] Satinsky E, Fuhr DC, Woodward A, Sondorp E, Roberts B. Mental health care utilisation and access among refugees and asylum seekers in Europe: a systematic review. Health Policy 2019;123(9):851–63. https://doi.org/10.1016/j.healthpol.2019.02.007.
[57] Suman A, Nehra R, Sahoo S, Grover S. Prevalence of loneliness and its correlates among patients with schizophrenia. Int J Soc Psychiatry 2023;69(4):906–15. https://doi.org/10.1177/00207640221141646.
[58] Teicher MH, Samson JA. Annual research review: enduring neurobiological effects of childhood abuse and neglect. J Child Psychol Psychiatry 2016;57(3):241–66. https://doi.org/10.1111/jcpp.12507.
[59] Cowell RA, Cicchetti D, Rogosch FA, Toth SL. Childhood maltreatment and its effect on neurocognitive functioning: timing and chronicity matter. Dev Psychopathol 2015;27(2):521–33. https://doi.org/10.1017/s0954579415000139.
[60] Berthelot N, Paccalet T, Gilbert E, Moreau I, Mérette C, Gingras N, et al. Childhood abuse and neglect may induce deficits in cognitive precursors of psychosis in high-risk children. J Psychiatry Neurosci 2015;40(5):336–43. https://doi.org/10.1503/jpn.140211.
[61] Mlay J, Paruk S, Tomita A, Lessells R. Engagement, disengagement and re-engagement in mental health services among young patients with first-episode psychosis: a scoping review. Early Interv Psychiatry 2025;19(10):e70100. https://doi.org/10.1111/eip.70100.
[62] Hajek A, Gyasi RM, Pengpid S, Peltzer K, Kostev K, Soysal P, et al. Prevalence of loneliness and social isolation amongst individuals with severe mental disorders: a systematic review and meta-analysis. Epidemiol Psychiatr Sci 2025;34:e25. https://doi.org/10.1017/s2045796025000228.
[63] Lamb HR, Weinberger LE. Some perspectives on criminalization. J Am Acad Psychiatry Law 2013;41(2):287–93.
[64] Buongiorno L, Mele F, Petroni G, Margari A, Carabellese F, Catanesi R, et al. Cognitive biases in forensic psychiatry: a scoping review. Int J Law Psychiatry 2025;101:102083. https://doi.org/10.1016/j.ijlp.2025.102083.
[65] Joyce DW, Kormilitzin A, Smith KA, Cipriani A. Explainable artificial intelligence for mental health through transparency and interpretability for understandability. NPJ Digit Med 2023;6(1):6. https://doi.org/10.1038/s41746-023-00751-9.

[66] Tortora L. Beyond discrimination: generative AI applications and ethical challenges in forensic psychiatry. Front Psych 2024;15:1346059. https://doi.org/10.3389/fpsyt.2024.1346059.
[67] Starke G, D'Imperio A, Ienca M. Out of their minds? Externalist challenges for using AI in forensic psychiatry. Front Psych 2023;14:1209862. https://doi.org/10.3389/fpsyt.2023.1209862.
[68] Nahm FS. Receiver operating characteristic curve: overview and practical use for clinicians. Korean J Anesthesiol 2022;75(1):25–36. https://doi.org/10.4097/kja.21209.