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Violent and non-violent offending in patients with schizophrenia: Exploring influences and differences via machine learning

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ABSTRACT

Objectives: The link between schizophrenia and violent offending has long been the subject of research with significant impact on mental health policy, clinical practice and public perception of the dangerousness of people with psychiatric disorders. The present study attempts to identify factors that differentiate between violent and non-violent offenders based on a unique sample of 370 forensic offender patients with schizophrenia spectrum disorder by employing machine learning algorithms and an extensive set of variables.
Methods: Using machine learning algorithms, 519 variables were explored in order to differentiate violent and non-violent offenders. To minimize the risk of overfitting, the dataset was split, employing variable filtering, machine learning model building and selection embedded in a nested resampling approach on one subset. The best model was then selected, and the most important variables applied on the second data subset.
Results: Ten factors regarding criminal and psychiatric history as well as clinical, developmental, and social factors were identified to be most influential in differentiating between violent and non-violent offenders and are discussed in light of prior research on this topic. With an AUC of 0.76, a sensitivity of 72% and a specificity of 62%, a correct classification into violent and non-violent offences could be determined in almost three quarters of cases.
Conclusions: Our findings expand current research on the factors influencing violent offending in patients with SSD, which is crucial for the development of preventive and therapeutic strategies that could potentially reduce the prevalence of violence in this population. Limitations, clinical relevance and future directions are discussed.
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1. Introduction

Violent behavior in individuals with schizophrenia spectrum disorders (SSD) poses a challenge for clinicians as they are confronted with an increasing number of forensic inpatients and are legally obliged to assess and manage the risk of violence in individuals receiving treatment. On the one hand, available actuarial violence risk assessment tools suffer from limited predictive power [1–3]; on the other hand, the origins of violent behavior in people with SSD are not yet sufficiently understood either, reflecting the difficulty of measuring rare but complex events related to a similarly rare illness affecting less than 1% of the population. However, most researchers and clinicians agree that violence is multifactorial and heterogeneous in nature, hence suggesting the existence of different pathways to violence [4]. Unravelling these pathways may facilitate the development of more accurate risk assessment and violence prevention strategies tailored to those with SSD, as it constitutes one of the most prevalent diagnoses in forensic clinics. Large demographic and epidemiologic studies have revealed that individuals with SSD tend to be more likely than other patient groups or people without mental illness to commit violent offences [5–7], but fail to provide robust predictive or explanatory models for schizophrenia-specific violence. The results of studies on the association of certain symptoms and violent behavior remain fragmented and inconclusive, which underlines the need for further research in this area.

Over the past decades, many researchers have been devoted to finding risk factors for violent behavior in people with SSD, thereby identifying a multitude of relevant parameters, which are commonly divided into static and dynamic risk factors [4,8]. Static risk factors mainly concern the past of the affected individual and relate to unchangeable conditions that are beyond the person's control. They include genetic and biological predispositions, male sex, younger age, physical or sexual abuse, early exposure to poverty, conduct disorder prior to age fifteen, a history of victimization, previous criminal activity, prolonged forensic hospitalization and coercive psychiatric treatment [9–14]. Violent behavior may partly be a product of those past experiences, with predisposing environmental conditions, desensitization and social learning playing a role [15]. Furthermore, traumatic experiences are recognized as a significant explanatory risk factor for the perpetration of violence in

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the mentally healthy general population and among mentally ill people [16]. The risk of people with both a trauma history and SSD committing violent offences is further increased by two or more times [17]. Dynamic risk factors can be modified and may therefore constitute potential targets for risk reduction efforts and therapeutic interventions. They include comorbid substance abuse, antisocial behavior, poor compliance with therapy, unemployment, higher overall symptom severity [11,12,18,19] and untreated psychotic symptoms, especially if the person feels threatened by them or fears losing control to external forces [4,20,21]. In this context, other studies found distrust and hostility, severe hallucinations, increasing disorganization of thought processes, and lack of insight into delusions and the disorder in general to be risk factors for violence [4,22]. Delusions per se are not related to violence, unless they are persecutory or involve intentional thoughts of committing violence [23]. Violent behavior may also be a direct response to the individual's perception of deprivation or punishment and is typically associated with feelings of frustration, fear, injustice and anger [4,24]. However, it should be noted that static risk factors cannot be considered completely independently of dynamic risk factors, because the former are often the prerequisite for the latter.

So far, various studies have provided a rather incomplete picture of people suffering from SSD engaging in violence. Differing definitions of violence adopted in previous studies may have led to such divergent results [25]. Some studies include threats and verbal attacks in their definition of violence [6], while others only consider direct physical aggression [26]. Since physical violence with the intent to bodily hurt or abuse another person is likely to have strong implications for political and clinical decisions, we decided to focus the present study on this definition and Swiss law (see Methods section for further details). Determining the relative impact of various risk factors on violent acts of people with SSD poses a considerable challenge for forensic psychiatry. Apparently, there are no direct causal links between psychiatric disorders and violence and a more refined approach is required for further examination. Previous studies have mostly compared violent offenders with SSD with non-violent patients from general psychiatry or with healthy controls. However, we suspect that there also exist significant differences in the expression of various factors between violent and non-violent offenders. In light of this, the aim of the present study is to (re-) explore and identify such factors, thus facilitating a more nuanced understanding of violence and more tailored violence prevention strategies. Based on an extensive database consisting of 370 patient records and more than 500 variables, machine learning (ML) seems to be the most appropriate statistical approach for our objectives. ML is capable of identifying non-linear relationships, thus making it suitable for analyzing and modelling complex phenomena such as violence. In previous studies on violent offending, different methodological frameworks were used, thereby limiting comparability, and few studies provided information on predictive accuracy of the evaluated statistical models. For this reason, another objective of this study was to use a more innovative statistical procedure with a good balance between specificity and sensitivity.

1.1. Aims of the study

The purpose of this exploratory study was to identify influencing factors that distinguish between violent and non-violent offences in a sample of forensic offender patients suffering from SSD by including a comprehensive set of variables and to provide a predictive value for such distinction.

2. Methods

2.1. Source of data and measures

The files of 370 offender patients diagnosed with SSD as defined in ICD-10 [27] or ICD-9 [28] who were admitted to the Center for Inpatient Forensic Therapies at the Zurich University Hospital for Psychiatry between 1982 and 2016 were analyzed retrospectively. Our complex database, containing an enormous range of different variables, has already been used in other studies and is part of a larger project in which forensic inpatients' medical files were extensively analyzed to gain insights into the still under-researched area of schizophrenia and offending. Based on the approach of data analysis via machine learning, we have been and are still aiming at exploring complex relationships in various specified research questions. Although the same database is the foundation for all analyses and there was some overlap in the variables examined in our studies, they also included a considerable number of unique variables that led to different results, and different theoretical and practical implications. Full details on data collection and processing can be found in Kirchebner et al. [29] and Günther et al. [30]. For an overview of sociodemographic, legal and clinical data of the study population, see Table 1.

2.2. Statistical procedures – Machine learning

Since this study was explorative in nature, supervised machine learning (ML) seemed to be the optimal method to identify the most important influencing factors of a multitude of variables and to determine the model with the best predictive power. To combat overfitting, a common obstacle in ML, we decided to split the database into training and test subsets and to apply a nested resampling approach. For a detailed description of ML in general and our statistical approach in particular, see Günther et al. [30]. Due to the differing objectives of the present study, procedural distinctions emerged, which will be explained in more detail below.

The outcome variable – severity of the index offence – was dichotomized into (1) *violent offence* and (2) *non-violent offence*. The following offences were considered as violent based on our definition (addressed in the Introduction) and Swiss law: homicide and attempted homicide, assault, rape, robbery, arson and child abuse. The category non-violent offence included threat, theft, damage to property, minor sexual offences (e.g. exhibitionism), drug offences, illegal gun possession and other minor offences (e.g. triggering false alarms or emergency brakes). One patient showed missing data on his index offence and was therefore excluded from the study leading to a reduction of cases to 369. Of

Table 1
Sociodemographic, legal and clinical data of the study population.

Variable description	Violent offence n/N (%) mean (SD)	Non violent offence n/N (%) mean (SD)
Age at admission	34.1 (10.4)	34.1 (9.6)
Male	270/294 (91.8)	68/75 (90.7)
Birthcountry Switzerland	140/294 (47.6)	27/75 (36.0)
Single (at time of index offence)	233/289 (80.6)	63/74 (85.1)
No employment (at time of index offence)	215/284 (75.7)	48/67 (71.6)
Diagnosis: Schizophrenia	241/294 (82.0)	52/75 (69.3)
Diagnosis: Schizoaffective disorder	21/294 (7.1)	5/75 (6.7)
Diagnosis: Acute psychotic disorder	17/294 (5.8)	11/75 (14.7)
Co-diagnosis SUD	215/294 (73.1)	54/74 (73.0)
Co-diagnosis: Personality disorder	42/293 (14.3)	5/74 (6.8)
Index offence (multiple entries possible)	108/294 (36.7)	
Murder and attempted murder	149/294 (50.7)	
Assault	40/294 (13.6)	
Sex offence	30/294 (10.2)	
Arson		
Robbery	23/294 (7.8)	
Theft	40/294 (14.6)	26/75 (34.7)
Threat	83/294 (28.2)	25/75 (33.3)
Offences against the controlled substance act	31/294 (10.5)	27/75 (36.0)

Note. SD = Standard deviation; SUD = Substance use disorder.

the remaining patients, 294 (79.7%) had committed a violent index offence and 75 (20.3%) had committed a non-violent index offence. Non-violent index offence was defined as the positive class, violent offence as the negative class. Splitting of the database resulted in a training data subset with 259 patients and a validation subset 110 patients. As the distribution of the violent/ non-violent offence result was not balanced (80% vs. 20%), the smaller subset (non-violent offence) was oversampled at a rate of 4.

After data processing, 519 possible predictor variables remained, which were filtered and thus reduced by random forest algorithms. Fig. 1 provides an overview of all methodological steps of data analysis.

3. Results

The performance measures of all trained models during the nested resampling procedure on the initial training dataset (70% of the total dataset) can be seen in Table 2. Gradient Boosting was identified as the best performing algorithm with a balanced accuracy of 70%.

The ten most indicative variables (code, description and distribution), which were identified by random forest testing and subsequently used for model building, can be seen in Table 3

The final gradient boosting model using these variables applied to the validation subset (30% of the total dataset) yielded a balanced accuracy of 67.83% and an AUC of 0.7640 (see Table 4) This model showed a sensitivity of 72.73%, thereby reflecting its ability to correctly classify the actual cases of non-violent index offences, and a lower specificity of 62.92%, indicating its ability to correctly identify those committing a violent index offence.

No dependencies between the variables were found when testing for multicollinearity. The importance of each variable in the gradient boosting model can be seen in Fig. 2.

The time spent in current forensic hospitalization and the age of first diagnosis of SSD were identified as the most indicative factors for the distinction between violent/ non-violent offences. Time spent in prison, olanzapine equivalent at discharge, PANSS total score at admission and discharge were also identified as factors influencing the model, as were previous convictions, actual or potential discharge, social isolation in adulthood, and poverty in childhood/ adolescence.

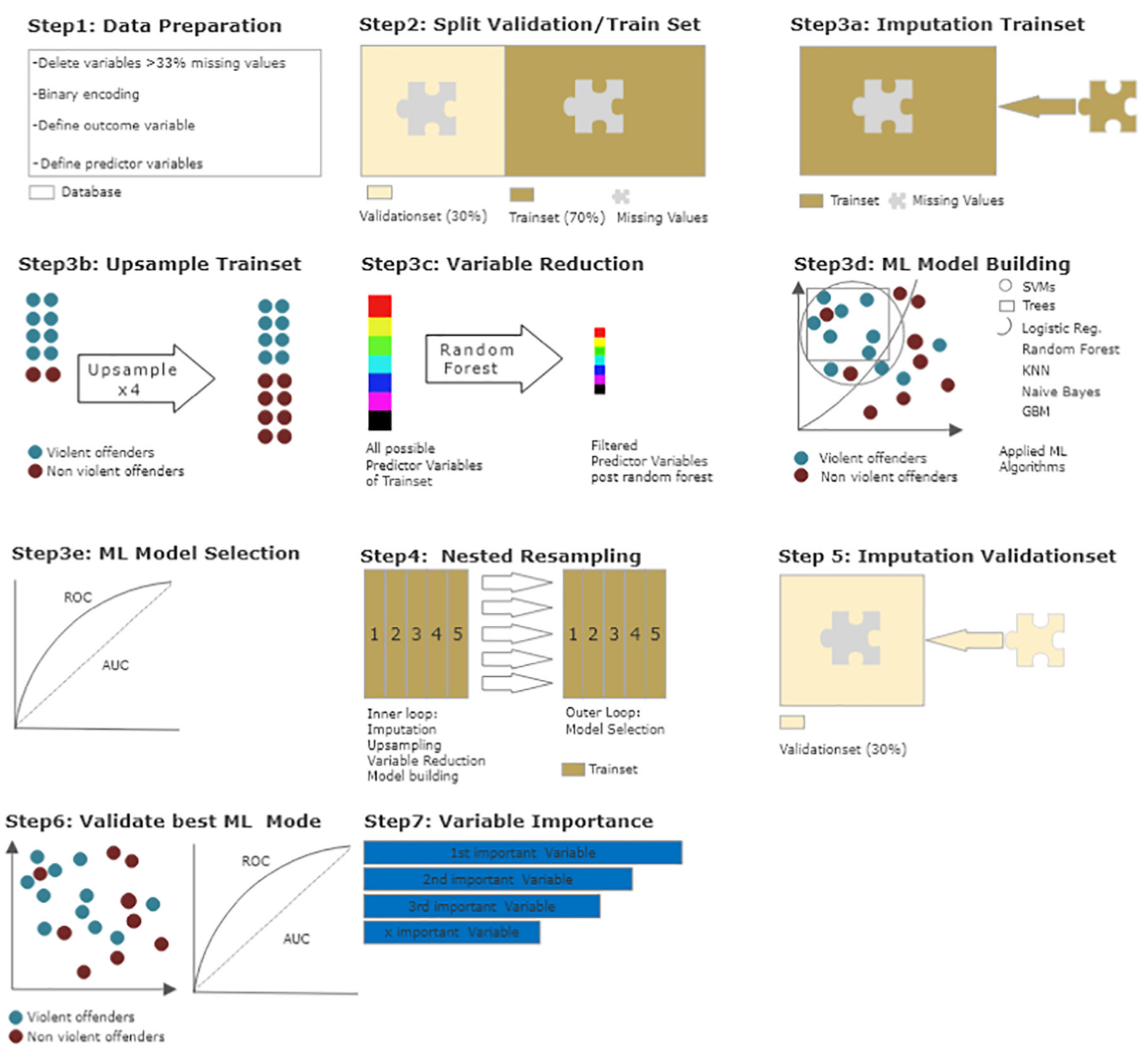

Fig. 1. Overview of statistical procedures. *Step 1 – Data Preparation*: Multiple categorical variables were converted to binary code. Continuous and ordinal variables were not manipulated. Outcome variable violent offence/non-violent offence and 519 predictor variables were defined. *Step 2 – Datasplitting*: Split into 70% training dataset and 30% validation dataset. *Step 3 a, b, c, d, e – Model building and testing on training data I*: Imputation by mean/mode; upsampling of outcome "non-violent offence" x4; variable reduction via random forest; model building via ML algorithms - logistic regression, trees, random forest, gradient boosting, KNN (k-nearest neighbor), support vector machines (SVM), and naive bayes; testing (selection) of best ML algorithm via ROC parameters. *Step 4 – Model building and testing on training data II*: Nested resampling with imputation, upsampling, variable reduction and model building in inner loop and model testing on outer loop. *Step 5a - Model building and testing on validation data I*: Imputation with stored weights from Step 3a. *Step 6 - Model building and testing on validation data II:* Best model identified in Step 3e applied on imputed dataset and evaluated via ROC parameters. *Step 7: Test for multicollinearity and ranking of variables by indicative power.*

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

Statistical procedure	Balanced accuracy (%)	AUC	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)
Logistic regression	68.38	0.6787	68.63	68.12	34.65	89.98
Tree	60.97	0.6259	47.06	74.88	31.58	85.16
Random Forest	58.19	0.7234	29.41	86.96	35.71	83.33
Gradient boosting	70.21	0.8026	68.22	72.20	39.04	89.70
KNN	59.30	0.6693	49.02	69.57	28.41	84.71
SVM	66.85	0.7223	58.82	74.88	36.59	88.07
Naive Bayes	68.63	0.7576	70.59	66.67	34.29	90.20

Note. AUC = area under the curve (level of discrimination); PPV = positive predictive value; NPV = negative predictive value; KNN = k-nearest neighbors; SVM = support vector machines.

Table 3
Absolut and relative distribution of indicative variables.

Variable	Violent offence	Non-violent offence
Time spent in current forensic hospitalization (in weeks) (mean, SD)	131.4 (140.7)	42.08 (75.8)
Age at schizophrenia spectrum disorder diagnosis (mean, SD)	27.1 (9.36)	29.1 (8.6)
Time spent in prison (before current hospitalization >1 year	94/264 (35.6)	14/69 (26.4)
Daily cumulative olanzapine equivalent at discharge (mean, SD)	19.6 (13.0)	17.8 (17.8)
PANSS Score at discharge (mean, SD)	27.0 (21.3)	19.4 (17.3)
PANSS Score at admission (mean, SD)	45.4 (21.5)	42.1 (17.9)
Any entries in the federal central criminal record	161/281 (57.3)	48/63 (76.2)
Discharge:		
Patient released	182/279 (65.2)	65/71 (91.5)
Release expected in more than one year	76/279 (27.2)	1/71 (1.4)
Social isolation in adulthood	181/266 (68.1)	45/53 (84.9)
Poverty in patient's childhood / youth	97/240 (40.4)	9/42 (21.4)

Note. SD = Standard deviation; PANSS = positive and negative syndrome scale (adapted measurements: symptom completely absent = 0, symptom discretely present = 1, symptom substantially present = 2).

Table 4
Final gradient boosting model performance measures.

Performance measures	%	95% Confidence Interval
Balanced Accuracy	67.83	[60.58, 74.25]
AUC	0.764	[0.6940, 0.8340]
Sensitivity	72.73	[62.02, 81.42]
Specificity	62.92	[52.98, 72.74]
PPV	65.98	[55.58, 75.10]
NPV	70.00	[58.58, 79.48]

Note. AUC = area under the curve (level of discrimination); PPV = positive predictive value.
NPV = negative predictive value.

4. Discussion

The aim of our exploratory study was to identify factors that distinguish between violent and non-violent offences committed by individuals with schizophrenia spectrum disorder in order to facilitate a better understanding of the relationship between violent offences and SSD. By employing machine learning algorithms and a unique database, we were able to build a model comprising ten factors. With an AUC of 0.76, a sensitivity of 72% and a specificity of 62%, a correct classification into violent and non-violent offences could be determined in almost three quarters of cases. However, it was unable to do so in more than a quarter of cases as an important limitation requiring caution in drawing definitive conclusions. Variables regarding criminal and psychiatric history as well as clinical, developmental, and social factors were identified to be most influential and are described in more detail below. Violent offenders spent more *time in forensic hospitalization*, which is in accordance with earlier findings [13,31–34] suggesting a link between serious violent offences and long-term forensic treatment. In line with this, the factors *expected discharge in more than 1 year* and *time in prison more than 1 year before current hospitalization* were also identified as important in detecting violent offenders in our sample. Patients who have committed violent offences may have been subject to more rigorous evaluations than those who have committed non-violent offences, as clinicians and courts may feel responsible for preventing further serious offences and if aftercare conditions do not appear optimal, they may be reluctant to recommend discharge [13]. However, the result that non-violent offenders had more *previous convictions* than violent offenders seems somewhat contradictory, but is consistent with earlier findings indicating that the most severe offence – homicide – is often committed later in life by patients with SSD who have no prior history of violence [35]. We further assume that non-violent offenders may be more likely to attract negative attention through socially inappropriate and bizarre behavior and to commit rather minor offences, which may lead to more contact with the legal system, but may also result in more psychiatric treatment (e.g. probation requirements) and regular monitoring. The factor *isolation in adulthood* was found to separate non-violent offenders from violent ones. It should be noted, however, that the violent offenders have also been predominantly isolated (84.9% non-violent vs. 68.1% violent). There may be subgroups of patients who are more likely to exhibit either externalizing or internalizing behavior, explainable by still upright behavioral inhibition capabilities in non-violent offenders and a higher limitation of the ability to suppress violent impulses in violent offenders [36]. This is also reflected by the clinical variables found to be important: higher *PANSS scores at admission and discharge*, higher *daily cumulative olanzapine equivalent antipsychotic dosage at discharge* and younger *age at SSD diagnosis*, with an average of 27 years for violent and 29 years for non-violent offenders. These findings indicate a more severe manifestation of the psychotic disorder and a potentially higher incidence of neurological impairment in violent offenders. Neurological dysfunction may be associated with reduced capacity for timely behavioral modification or self-correction and may also impair response to treatment, as neurological dysfunction is thought to reduce the effect of antipsychotic drugs [37,38]. However, others argue that more severe brain abnormalities are related to social withdrawal, while less severe abnormalities are related to better social functioning, more social contacts and violent behavior [39–41]. This inconclusive result again points to the existence of different patient subgroups and requires further neuropsychiatric research to detect even subtle variations at a cellular level and, in conjunction with observations at the behavioral level, to gain a more comprehensive understanding of the processes involved in violent behavior. Finally, our analysis identified *childhood poverty* in patients as influencing factor for violent offending, which supports previous research. Individuals exposed to poverty at a young age may, for example, experience poor pre- and postnatal care, particularly with regard to nutrition, and less cognitive stimulation, which may both contribute to cognitive difficulties that affect them throughout their lives [42]. Poverty is therefore important in that it provides a context in which violent behavior can unfold. The link between poverty, SSD and violence can thus best be understood as being the result of increased exposure to a range of risk factors, both in childhood and adulthood, which are disproportionately more prevalent among poorer

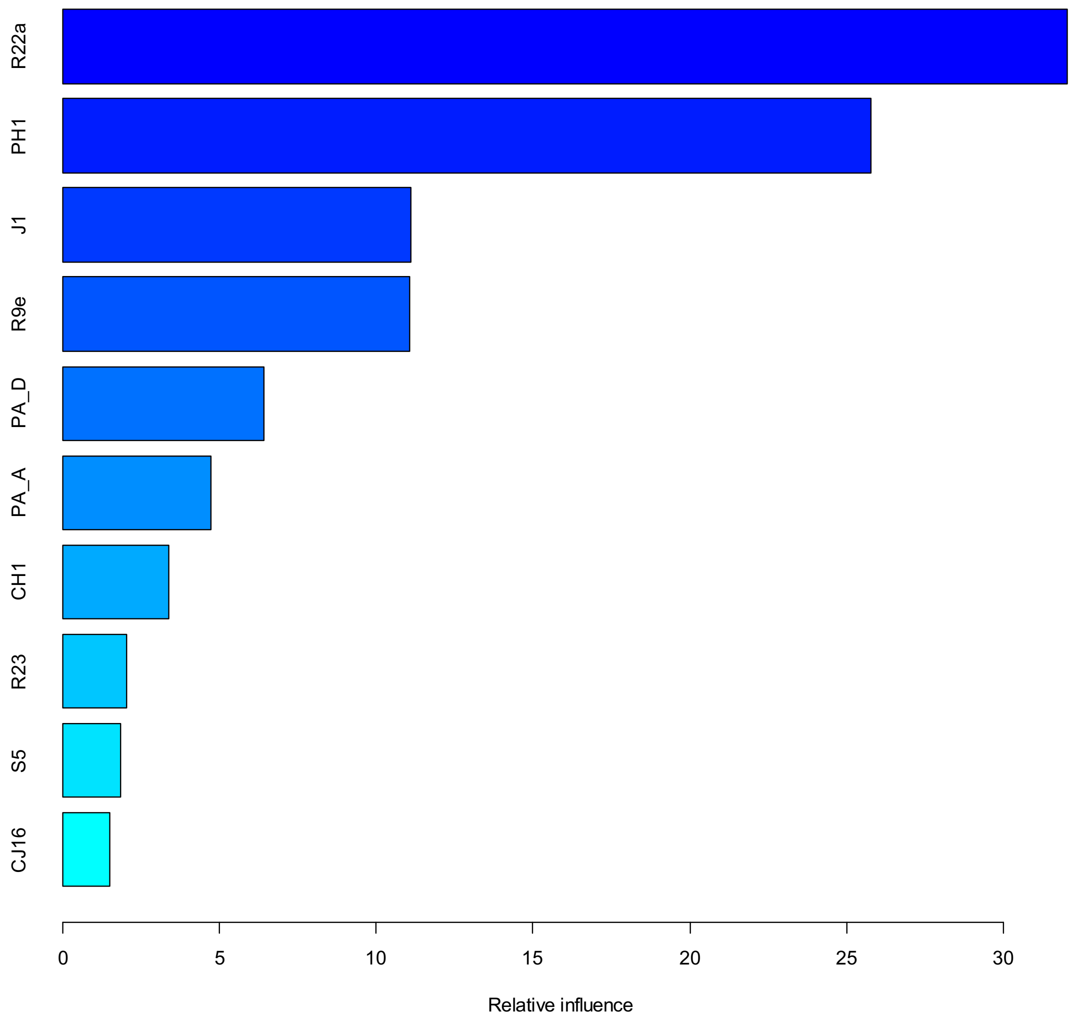

Fig. 2. Variable importance of final model. R22a = Time spent in current forensic hospitalization (in weeks); PH1 = Age at SSD diagnosis; J1 = Time spent in prison >1 year; R9e = Daily cumulative olanzapine equivalent at discharge; PA_D = PANSS Score at discharge; PA_A = PANSS Score at admission; CH1 = Any entries in the federal central criminal record; R23b = Expected Release; S5 = Social isolation in adulthood; CJ16 = Poverty in patient's childhood / youth.

people [43]. It is worth noting that substance abuse was not found as a differentiating factor in this analysis. This is inconsistent with previous findings that have linked substance abuse to a higher likelihood of violence in SSD patients [5,12,44,45] and requires further clarification.

With the exception of PANSS scores and antipsychotic medication, all factors found are static and therefore hardly or not at all modifiable. What may be modified, is the patients' perception of these experiences via more individually tailored therapeutic approaches, which consider their unique history. Our results indicate that there is no deterministic and monocausal pathway to violence in people with SSD, but that there are most likely different subgroups of patients. In this respect, we emphasize the need for a precise anamnesis and accurate documentation to enable valid assessment of the risk of future violence [40]. A better understanding of the patients' past and present could be helpful for the development of more subgroup-specific preventive and therapeutic approaches and possibly reduce the prevalence of violent behavior.

4.1. Limitations

The present analysis was based on retrospectively collected data of high quality. Nevertheless, distortions in the medical files could not be completely excluded. This also involves the use of a PANSS-adopted scale for content analysis of psychopathological data, which in some cases was recorded before the publication of said instrument, and also the reduction of complex variables to a dichotomous form, resulting in some information loss. While the factors found may suggest associations with the outcomes, they do not imply causality, and before basing clinical decisions on the results presented here, future studies should validate the identified model and preferably be conducted in different cultural and legal settings.

ML achieves particularly good results with large datasets and it should therefore be noted that the 370 patients analyzed represent a rather modest quantity in this context and thus, despite cross-validation, overfitting remains a limitation to the interpretability of this study.

4.2. Conclusions

Our findings expand the current research on influential factors for violent offending in patients with SSD, which is beneficial for the development of preventive and therapeutic strategies that could potentially reduce the prevalence of violent offences in said population. In view of these considerations and with the aim of examining hitherto unexplored connections between the various preconditions and determinants of violence in a more systematic and comprehensive manner, the potential of machine learning for the explorative analysis of patient data is increasingly recognized in psychiatric research [18,46–49]. Its usability in the forensic-psychiatric context is supported by the current study, examining differences between violent and non-violent offenders in a sample of 370 inpatients with SSD.

Conflicts of interest

None.

Ethics declarations

This study was reviewed and approved by the Ethics Committee Zurich [Kanton Zürich] (committee's reference number: KEK-ZH-NR 2014–0480). The study complied with the Helsinki Declaration of 1975, revised in 2008. This is a retrospective study. For this type of study formal consent is not required.

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Data availability statement

The dataset generated and analyzed during the current study are available from the corresponding author on reasonable request.

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