Schizophrenia and substance use disorder: Characteristics of coexisting issues in a forensic setting

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Schizophrenia and substance use disorder: Characteristics of coexisting issues in a forensic setting

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ABSTRACT

Background and aims: Recent research has identified higher prevalence of offending behavior in patients with comorbid schizophrenia spectrum disorder (SSD) and substance use disorder (SUD) compared to patients with SSD only and to the general population. However, findings on the subgroup of patients with SUD, SSD and offending behavior in forensic psychiatric care are scarce and inconsistent. The present study used machine learning to uncover more detailed characteristics of offender patients in forensic psychiatric care with comorbid SSD and SUD.

Methods: Using machine learning algorithms, 370 offender patients (91.6 % male, mean age of M = 34.1, SD = 10.2) and 558 variables were explored in order to build three models to differentiate between no substance use disorder, cannabis use disorder and any other substance use disorder. To counteract 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 validated on the second data subset.

Results: Distinguishing between SUD vs. no drug use disorder yielded models with an AUC of 70 and 78. Variables assignable to demographics, social disintegration, antisocial behavior and illness were identified as most influential for the distinction. The model comparing cannabis use disorder with other substance use disorders provided no significant differences.

Conclusions: From a clinical perspective, offender patients suffering from schizophrenia spectrum and comorbid substance use disorder seem particularly challenging to treat, but initial differences in psychopathology will dissipate over inpatient treatment. Our data suggest that offender patients may benefit from appropriate treatment that focuses on illicit drug abuse to reduce criminal behavior and improve social integration.

1. Introduction

Over the last decades, many studies suggested a higher risk and incidence of (violent) offending behavior (OB) among patients with schizophrenia spectrum disorder (SSD) compared to the general population (Volavka, 2013). Various clinical and non-clinical risk factors, such as age, sex and socioeconomic status (Swanson et al., 2006) seem to have impact on this risk. Utilizing knowledge of the general psychiatric population and focusing particularly on OB, SSD is being discussed as one of the most frequently diagnosed disorders in forensic psychiatric patients (de Tribolet-Hardy and Habermeyer, 2016; Fazel et al., 2014; Jansman-Hart et al., 2011). However, other results suggest that the actual link between SSD and offending may not be as high as generally expected, unless comorbid substance use disorder (SUD) is present (Fazel et al., 2009; Grann and Fazel, 2004).

A recent review and meta-analysis reported a lifetime comorbidity of 42 % (48 % in males, 22 % in females) between SUD and SSD and an earlier age of SSD onset (2.1 years) in those with an SUD (Hunt et al., 2013).
The prevalence of comorbid SUD was lower in Asian countries than in Australia and Western countries, which may be due to stricter law enforcement and cultural differences (Hunt et al., 2018). The rate of violent OB in individuals with both, SSD and SUD, was found to be significantly higher than in those with SSD only, which resulted in adjusted ORs of 4.4 (95 % CI 3.9–5.0) for violent OB in patients with SSD and SUD and 1.2 (95 % CI 1.1–1.4) for patients with SSD only (P < .001 for interaction) (Fazel et al., 2009).

When the relationship between SUD and OB has been explored in disregard of other psychiatric comorbidities, a medium effect size (grand weighted mean effect size of d = 0.45, 95 % CI [0.36, 0.54], p < .001) was confirmed (Duke et al., 2018). Factors associated with the pharmacodynamics of substances used as well as social, environmental and lifestyle factors contributing to OB (including the use of violence to obtain substances or money for substances) were identified (Boles and Miotto, 2003). In a recent umbrella review incorporating 22 meta-analyses, a pooled OR of 7.4 (95 % CI 4.3–12.7) was found for violent OB in individuals with SUD (Fazel et al., 2015). The relationship between SUD and OB was also explored for specific substances wherein the connection between alcohol and violent OB became particularly apparent (Norrstrom and Pape, 2010; Popovici et al., 2012). In a Swedish total population study (Fazel et al., 2014), the hazard ratio for OB in individuals with alcohol use disorders was 9.0 for men (95 % CI 8.2–9.9) and 19.8 for women (95 % CI 14.6–26.7), confirming similar findings from a large Australian longitudinal study (Boden et al., 2012). It was also found that alcohol and cocaine use disorders were more strongly linked to intimate partner violence than opioid or cannabis use disorders (Chermack et al., 2011; Smith et al., 2012). Other studies confirmed a relationship between OB and opioid use, OB and tranquilizer use, but not OB and hallucinogen use (Friedman et al., 2001). The relationship between OB and use of cannabis was examined most frequently, with twelve measures of association from eight studies, of which five showed an increased risk of interpersonal violence, two showed mixed results, and five showed no association (McGinty et al., 2018). A strong link between cannabis use and SSD has also been reported, concluding that cannabis use is likely to increase the risk of SSD (Malcolm et al., 2011; Schubart et al., 2010; Semple et al., 2005; Vaucher et al., 2018). Furthermore, cannabis use in adolescence may play a role in the development of OB in psychosis (Moulin et al., 2020). In summary, prior research has been able to establish a relationship between SUD, SSD and OB (Pickard and Fazel, 2013). Therefore, therapy recommendations aim at improved treatment of SSD in forensic psychiatric patients as a preventive measure for relapse and re-offending, highlighting the significant influence of appropriate forensic psychiatric care (Pickard and Fazel, 2013). However, more research is needed on the subgroup of patients with SUD, SSD and OB in forensic psychiatric care. The relationship between cannabis use disorders, SSD and OB deserves particular attention, since findings from prior research are highly inconsistent (McGinty et al., 2018; Mills, 2003; Moulin et al., 2020; Vaucher et al., 2018).

Consequently, the objectives of this exploratory study were to identify factors that differentiate between patients with and without SUD and patients with cannabis abuse alone in a group of forensic psychiatric patients suffering from SSD and to quantify a predictive value for said distinction. A more detailed understanding of the characteristics of patients with SUD, SSD and violent behavior in forensic care will allow for more targeted treatment and prevention. Due to the complexity of interactions between SSD, SUD and violence and the fact that our dataset contains a large number of different variables, an innovative approach to data analysis is necessary. Supervised machine learning (ML) allows the analysis of large amounts of data, and attempts to uncover previously unseen relationships between variables, which seems appropriate for our investigation of characteristics of patients with SUD, SSD and violent behavior.

1.1. Machine learning

As a descendant of artificial intelligence, ML is a promising technique to analyze larger collections of biological and clinical data than classical statistical methods in order to identify relations. Based on algorithms trained to detect relations between variables, previously unknown interactions can be made visible (Gui and Chan, 2017; Henglin et al., 2017). In the medical field, machine learning could improve screening, diagnostic, therapeutic and prognostic efforts. This might constitute a potential benefit for increasing efficiency in health care provision, while simultaneously reducing costs and decreasing the burden on physicians. However, there are some difficulties and challenges in applying ML in the medical field: Collecting large amounts of high-quality unbiased data, discomfort in trusting machines making health care decisions and accepting the risks of machine error (which may be less frequent than human error) (Deo, 2015).

2. Methods

2.1. Setting and sample

The files of 370 offender patients diagnosed with schizophrenia spectrum disorder were analyzed retrospectively. SSD was defined using ICD-10 (World Health Organization, 2016) or ICD-9 (World Health Organization, 1978) criteria. The patients were admitted to the Center for Inpatient Forensic Therapies at the Zurich University Hospital for Psychiatry between 1982 and 2016. A trained independent physician systematically reviewed all case files and conducted a directed qualitative content analysis (Hsieh and Shannon, 2005). A second trained independent rater encoded a random subsample of 10 % of cases to assess inter-rater reliability. Cohen’s Kappa (Brennan and Hays, 1992) was 0.78, which can be regarded as substantial (Field, 2013). The content analysis employed a questionnaire and rating protocol for coding based on the extended (Habermeyer et al., 2011; Kutscher et al., 2009) set of criteria proposed by Seifert (Seifert and Leygraf, 1997). For full details on data collection and processing, see Kirchbener et al. (2020) and Günther et al. (2020). SUDs were also diagnosed according to ICD-9 or ICD-10 criteria. Patients who had no comorbidity in terms of a SUD (no ICD-10, chapter F1x or ICD-9, chapters 303–305) were defined as (1), no SUD. Patients who had a secondary diagnosis of illegal use of cannabis (ICD-10-F12.1/12.2 or ICD-9 304.3/305.2) were defined as (2), only cannabis use disorder. Finally, patients who had any secondary diagnosis of SSD (also multiple diagnoses and cannabis use disorder plus another SSD; any or in combination ICD-10 F1x or ICD-9 303–305) were defined as (3), any SSD.

Of the total study population, 100 (27 %) offender patients had no SUD and 269 (73 %) had some SUD. Among the 269 with some illegal SUD, 85 (32 %) reported only cannabis use. One patient was excluded due to insufficient information. A set of 558 variables were defined as predictor (independent) variables which covered the following domains: social-demographic data, childhood/ youth experiences, psychiatric history, past criminal history, social and sexual functioning, details on the offence leading to forensic hospitalization, prison data, particularities of the current hospitalization and psychopathological symptoms by closely adopting the positive and negative symptom scale (PANSS), whereby symptoms were divided into the usual 30 sub-categories and rated on a scale (completely absent, discretely present or substantially present).

2.2. Procedure and measures

Since this study was explorative in nature, ML seemed to be the optimal method to identify the most important influencing factors on the relationship between SSD, SUD and OB. All steps were performed using R version 3.6.3. and the MLR package v2.171 (Bischl et al., 2016). CI calculations of the balanced accuracy were conducted using MATLAB.
R2019a (MATLAB and Statistics Toolbox Release 2012b, The MathWorks, Inc., Natick, Massachusetts, United States) with the add-on “computing the posterior balanced accuracy” v1.0 (Brodersen et al., 2010). To prevent overfitting, a common obstacle in ML, we decided to split the database into training (70%) and validation (30%) subsets and to apply a nested resampling approach on the training dataset. The training database is further divided into inner and outer loops. In the inner loop imputation, balancing if necessary (see below), filtering of the most important variables and finally ML modeling with the standard hyperparameters of the MLR package are performed. In the outer loop the ML models are tested on the data and the best model is selected. Both of these loops are embedded in a 5-fold cross-validation. Finally, the best model is selected and tested again on the validation dataset, which remains unmanipulated except for an imputation of the stored weights from the previous imputation of the training dataset. An overview can be found in Fig. 1.

For a detailed description of ML in general and our statistical approach in particular, see Günther et al. (2020). Due to the differing objectives of the present study, procedural distinctions emerged, which will be explained in more detail below.

Three different dichotomic outcome (dependent) variables were defined for three different machine learning models: (Model 1) no SUD versus any SUD (including cannabis), (Model 2) no SUD versus cannabis use disorders only and (Model 3) any SUD (excluding users of cannabis only) versus cannabis use disorders only.

In a next step, the initial database was split up into three subsets only differing in the dependent variables mentioned before (1, 2, 3). All statistical steps were performed on all three databases individually.

In model 1 the distribution of no SUD – any SUD was not balanced (27 % vs. 72.7 %). The smaller subset was oversampled at a rate of 2.5. Model 2, no SUD – only cannabis use disorders was balanced (45.9 % vs. 54.1 %), requiring no further adjustment. Model 3, any SUD – only

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**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 variables NO SUD/SUD/Cannabis abuse or addiction and 558 predictor variables were defined.  

*Step 2 – Datapartitioning:* 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; 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 5 – 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 validation dataset and evaluated via ROC parameters.  

*Step 7:* Sensitivity analysis and ranking of variables by indicative power.
cannabis use disorders, was not balanced (68.4 % vs. 31.6 %). Therefore, the smaller subset was oversampled at a rate of 2.

The step of filtering variables and their reduction was performed with a random forest algorithm, reducing the initial 558 predictor variables to the 15 most important for each model.

3. Results

The algorithms’ performance measures for each of the three models during the nested resampling procedure on the initial training datasets (70 % of the total dataset) can be seen in Table 1. Both, for model 1 comparing SUD vs. no SUD and model 2 comparing cannabis use disorders vs. no SUD, naïve bayes was identified as the best performing algorithm. Both models reached viable performance measures with a balanced accuracy/ AUC of 68/ 0.75 for model 1 and 72/ 0.79 for model 2.

All algorithms for model 3, with the best reaching an AUC of only 0.58, failed in terms of model performance requirements. Therefore, model 3 was excluded from further analysis.

The 15 most indicative variables (code, description and distribution), which were identified by naïve bayes for both models and subsequently used for model building, are presented in Tables 2 and 3.

The final naïve bayes models using these variables applied to the complete dataset (level of discrimination); PPV = positive predictive value; NPV = negative predictive value; KNN = k-nearest neighbors; SVM = support vector machines.

Table 1

| Variable code | Variable description | Drug Abuse | No Drug Abuse |
|---------------|----------------------|------------|--------------|
| D6, mean, SD  | Age of Pat. at crime | 30.02      | 37.27        |
| PH1, mean, SD | Age at which the F2x diagnosis was given | 26.19 | 33.06       |
| PH2, mean, SD | Age at which the patient showed first symptoms of the F2x diagnosis | 22.46 | 28.11       |
| SD14 | Offspring | 47/255 | 46/99 |
| SD1, mean, SD | Age at admission | 32.19 | 39.55        |
| SD5a | marital status: married | 68/265 | 52/98        |
| CH1 | Are there any entries in the federal central criminal registry prior to the index offence (offence leading to forensic hospitalization) | 169/248 | 40/96 |
| CH2 | More than 1 crime in federal central criminal registry | 131/167 | 22/40 |
| PH19b, mean, SD | Age at first inpatient treatment before investigated offence | 23.47 | 29.3        |
| CH3, mean, SD | Age at first entry in the federal central criminal registry | 22.93 | 30.92 |
| J1 | More than 1 year in prison | 118/244 | 23/98 |
| PA_A, mean, SD | PANNS Score at admission | 24.42 | 22.21 |
| R22a, mean, SD | Time spent in forensic hospital (in weeks) | 115.98 | 106.40 |
| R9, mean, SD | Olanzapine equivalent dose above the maximum recommended in guidelines | 19.71 | 18.07 |
| S8d | Private (non-institutionalized) housing | 25/238 | 37/93 |

Table 2

| Variable code | Variable description | Drug Abuse | No Drug Abuse |
|---------------|----------------------|------------|--------------|
| D6, mean, SD  | Age of Pat. at crime | 30.02      | 37.27        |
| PH1, mean, SD | Age at which the F2x diagnosis was given | 26.19 | 33.06       |
| PH2, mean, SD | Age at which the patient showed first symptoms of the F2x diagnosis | 22.46 | 28.11       |
| SD14 | Offspring | 47/255 | 46/99 |
| SD1, mean, SD | Age at admission | 32.19 | 39.55        |
| SD5a | marital status: married | 68/265 | 52/98        |
| CH1 | Are there any entries in the federal central criminal registry prior to the index offence (offence leading to forensic hospitalization) | 169/248 | 40/96 |
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| S8d | Private (non-institutionalized) housing | 25/238 | 37/93 |

Note. SD = Standard deviation; PANSS = positive and negative syndrome scale.

4. Discussion

The objective of this study was to identify factors that differentiate between patients with and without SUD and those with cannabis abuse alone in a group of forensic psychiatric patients with SSD, since previous
Absolute and relative distribution of indicative variables for model 2 on complete dataset – cannabis use disorders vs. no substance use disorder.

| Variable code | Variable description | Cannabis Abuse | No Drug Abuse |
|---------------|----------------------|----------------|--------------|
| D6 (mean, SD) | Age of Pat. at crime | 29.02 (9.24) | 37.27 (10.77) |
| PH1 (mean, SD) | Age at which the F2x diagnosis was given | 25.72 (8.05) | 33.06 (10.62) |
| PH2 (mean, SD) | Age at which the patient showed first symptoms of the F2x diagnosis | 22.09 (13.4) | 28.11 (6.35) |
| SD14 | Offspring | 11.82 (11.4) | 46.99 (46.3) |
| SD1 (mean, SD) | Age at admission | 31.06 (9.1) | 39.55 (11.27) |
| SD5a | Marital status: married | 17.84 (20.2) | 52.98 (53.1) |
| SD12a | Low income job | 78.84 (92.9) | 67.97 (69.1) |
| CJ5 | Disciplinary problems in the patients childhood/youth | 35.63 (55.6) | 18.70 (25.7) |
| PH19b (mean, SD) | Age at first inpatient treatment before investigated offence | 23.35 (7.27) | 29.3 (8.93) |
| DZ2 | Dissocial behavior during current hospitalisation: negative behavior towards fellow patients | 34.82 (41.5) | 27.10 (27) |
| DZ10 | Dissocial behavior during current hospitalisation: constant breaking of rules | 24.83 (28.9) | 15.10 (15) |
| PA21 (mean, SD) | PANNS at admission: Motor retardation | 35.63 (55.6) | 18.70 (25.7) |
| PA25 (mean, SD) | PANNS at admission: Poor attention | 32.83 (38.6) | 53.94 (56.4) |
| PA28 (mean, SD) | PANNS at admission: Poor impulse control | 32.83 (38.6) | 53.94 (56.4) |
| SD8d | Private (non-institutionalized) housing | 8.77 (10.4) | 37.93 (39.8) |

Note. SD = Standard deviation; PANNS = positive and negative syndrome scale.

Table 4

Final naïve bayes model performance measures on validation dataset.

| Performance measures | % 95 % Confidence Interval |
|----------------------|----------------------------|
| Model 1: Substance use disorder vs. no substance use disorder | Balanced Accuracy: 67.02 [66.29, 67.75] |
| | AUC: 0.7016 [0.5904, 0.8128] |
| | Sensitivity: 94.03 [89.65, 98.07] |
| | Specificity: 40.00 [24.35, 57.79] |
| | PPV: 77.78 [51.92, 92.63] |
| | NPV: 75.00 [64.15, 83.53] |

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.

(Alozai and Sharma, 1989; Howes et al., 2004; Kalra et al., 2012; Patel et al., 2014; van Os et al., 2010). Regarding demographic data, our study found patients with SUD (including cannabis) to be younger when a psychiatric diagnosis was first recorded and at first entry into the federal central criminal registry than those without SUD. These results confirm prior findings (Hasan et al., 2020; Ringen et al., 2016) and might be explained by patients with SSD and SUD being younger when initially showing psychotic symptoms and being diagnosed with SSD (Sara et al., 2013; Stefanis et al., 2014). Additionally, our results suggest that patients with any SUD are less likely to be married, have children, or live in private (non-institutionalized) housing and more likely to work in low-wage jobs (i.e., below the Swiss average according to government publications; Swiss Confederation, Federal Office of Public Health, n.d.). These results imply a lower socio-economic status of patients with any SSD, as has been proposed in previous research (Cerdà et al., 2016; Kavanagh et al., 2004).

As cannabis consumption in young people is rising, studies have discussed a higher risk of emotional and behavioral problems in minors consuming cannabis and an associated higher vulnerability for dissocial behavior (McArdle, 2006). Our results confirm this theory, as we found more behavioral and disciplinary problems in childhood and adolescence among patients with cannabis use disorder. It is also suggested that cannabis use in adolescence carries a greater risk of development of psychosis than use in adulthood, as the developing brain is particularly sensitive (Malcolm et al., 2011; Schubart et al., 2010). A recent study by Huber et al. stated that patients with early onset psychosis may be more likely to have increased levels of agitation, dissocial personality disorder, forensic history and SSD (Huber et al., 2016). Confirming these findings, in our sample patients with SSD are more likely to be registered in the federal central criminal registry and have been convicted of more than one offence compared to non-users. In the subgroup of patients with cannabis use disorders, our investigations showed more dissocial conduct compared to non-users, such as negative behavior towards fellow patients and constant breaches of rules on the ward, which was also observed in earlier studies (Ford et al., 2009; Mariani et al., 2008).

Some results specifically concern the psychopathology of the three groups explored (no SSD, cannabis use only, any SSD). Past research indicated that comorbid SSD in patients with SUD can lead to more severe (positive) psychotic symptoms (Baeza et al., 2009; Brunette et al., 2018). Confirming these results, our study also found a higher symptom severity in patients with SSD and any SSD at admission in comparison to those without SSD. The duration of forensic psychiatric inpatient treatment of patients with any SSD was longer and they were more...
frequently discharged with olanzapine equivalent dosages above the maximum recommended in guidelines (25.72 mg, the equivalent of 1000 mg of chlorpromazine). Prior research has also reported doses of antipsychotic agents in forensic psychiatric care to be higher than in general psychiatry (Howner et al., 2018). Summarizing these findings and comparing them with previous literature, patients with SUD and SSD appear to have more severe symptoms and histories of illness (Crean et al., 2011). Yet, there were no significant differences of symptom severity at discharge between patients with and without SUD. This could be interpreted as a result of successful treatment, since the subgroup of patients with SSD and SUD appear to be more symptomatic when they enter treatment, compared to non-users. This is most likely due to the fact that recommendations from existing research advising to treat SUD during psychiatric hospitalization have already been implemented (Pickard and Fazel, 2013). Symptoms such as motor retardation, poor attention and poor impulse control seem more distinctly present in the subgroup of patients with cannabis use disorder compared to the other two groups (i.e., any SUD/ no SUD). Prior studies also reported cannabis users may show significant impairment in psychomotor performance (Sosker et al., 2013; Desrosiers et al., 2015) and cognitive functions, even though severity can vary (Crean et al., 2011).

Finally, the different models did not identify any variables from the domain of current offending behavior as the major influencing factors. Consequently, the presence and type of SUD also did not appear to be a determining influence on the type and severity of, or approach to, offending. Except for the age-component in psychiatric history and disciplinary difficulties in childhood and adolescent history, these domains also played a subordinate role.

In summary, forensic patients with SSD and SUD appear to have complex characteristics resulting in specific needs. Our research leads to the conclusion that in the sample of forensic care patients examined here, the biggest issue seems to be the SUD itself and distinguishing between cannabis use disorders and other SUD may be less clinically relevant. The comorbidity of substance use in forensic care patients with SSD seems to have a negative impact on the time of SSD onset, the severity of symptoms and the cognitive functioning of these patients. Furthermore, they appear to be prone to more dissocial behavior during forensic psychiatric treatment. Our findings suggest that, despite the complexity of symptoms and behaviors, this specific subgroup of patients would benefit from intensive treatment for SUD while in the forensic setting (Fazel et al., 2009; Gendel, 2006).

4.1. Limitations

As a retrospective analysis of data, this study has several limitations, such as selection and information biases (Hoffman, 2007). Retrospective file research requires large sample sizes for high quality and reliable results. We were able to collect data from 370 patients in forensic care with SSD and OB, which can be considered a large amount of data on such a specific patient subgroup. Nonetheless, when using ML, this appears to be a small sample size which may entail some issues: The algorithms are dependent on the data they are fed and hence, the obtained models can be influenced by possible biases in the underlying data. This could be the case, for example, in the definition of the outcome variable. The diagnosis of SUD in the files was based on ICD-coding, but the assessment of symptoms and the delineation of different forms of SUD may differ over such a long period of observation.

Algorithms attempting to predict criminal behavior and violence
have been shown to be particularly vulnerable to racial and socioeconomic biases (Angwin et al., 2016; Asher and Arthur, 2017; Broussard, 2018; Davey, 2016; Lum and Isaac, 2016; O’neil, 2016; Tortora et al., 2020). Authors of the current study have zero tolerance for such inclinations and have taken great precautions to avoid such bias. The impact of these kinds of influences in forensic psychiatry, where treatment of human beings and legislation are at stake, is large and must be treated with utmost caution. Consequently, results of the present study are seen less as a modeling tool for predictions, but more as a starting point for future prospective studies (with a possible focus on prediction). Therefore, collecting more data on this specific subgroup of patients seems to be crucial for further research. Additionally, our sample size was not big enough to distinguish further subgroups within the subgroup of patients with a SUD and determine differentiating factors between the individual substances (i.e., cocaine vs. heroin). From a methodological perspective, we were able to avoid overfitting by employing a nested resampling model (Saria et al., 2018). Nevertheless, our final model should be confirmed in other patient samples to determine a more accurate AUC.

4.2. Conclusions

Treatment of SUD issues are a high priority in forensic psychiatric settings. Our findings highlight that patients in these settings have high rates of coexisting mental health disorders and SUD. SUD may be linked to earlier age onset of psychosis and OB. For cannabis use, psychosis and OB may be associated with dissocial personality patterns. Often patients with SSD and SUD present to forensic settings with more severe symptoms and require longer inpatient treatment. Upon discharge however, there appear to be no significant differences of symptom severity between patients with and without SUD. Nevertheless, patients with coexisting latent issues in forensic psychiatric settings might be discharged on higher doses of antipsychotic medications. Higher dosing may increase this populations likelihood of metabolic syndrome and/or shortened life expectancies.

The risk of relapse is high when patients first leave forensic psychiatric treatment and return to contexts associated with past consumption. Therefore, (continuation of) SUD treatment should be offered seamlessly after discharge from the forensic psychiatric hospital, as the risk of relapse and other negative consequences, including the risk of premature death, is significantly increased during this transitional period (Pickard and Fazel, 2013).

Lastly, patients in forensic settings with coexisting SUD and SSD may be more likely to be socially isolated and living in lower socio-economic circumstances. Discharge planning should not only focus on ongoing alcohol or other drug treatment, but on building social networks and creating opportunities for employment and income to enhance quality of life and to prevent relapse and recidivism.

4.3. Future perspectives

In addition to the prospective testing of our model in other clinical populations, ML offers the potential to address other complex questions on SUD, SSD and OB and thus to deepen the still sparse basic knowledge. For example, prospective studies could analyze data on use of illicit substances for possible self-medication or complex questions about gene
expression. Also, the ability of ML to provide correct psychiatric diagnoses could be compared to diagnoses made by trained therapists. In general, ML is still in its infancy. Future automated implementation in clinical settings requires more studies, good modeling with high sensitivity and specificity, and ultimately a societal discourse on when a model can be considered usable or what error rate is acceptable (compared to human decision-making).

Declaration of Competing Interest

The authors report no declarations of interest.

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