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Constellations of youth criminogenic factors associated with young adult violent criminal behavior

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Abstract

This study identified constellations of childhood risk factors associated with violent criminal behavior in early adulthood. Police data were used to sample violent and nonviolent offenders from a population of young adult males with a history of juvenile probation. Risk factors were retrieved from their juvenile probation files. A single classification tree analysis organized these into a decision tree for violent criminal behavior with good predictive accuracy. Two constellations of risk factors were associated with a high risk of violent criminal behavior. The first consisted of juvenile delinquents who had been moderately involved with criminal peers, who had committed offenses under the influence of drugs, and who came from a dysfunctional family. The second was characterized by having been severely involved with criminal peers and having had criminal family members. Presenting with depressive symptoms in childhood was associated with a low risk of violent criminal behavior. These constellations bear clinical importance as they provide targets for personalized interventions.

Keywords: Violent crime, Juvenile offenders, Criminogenic risk factors, Decision tree analysis, CHAID, Early adulthood

Introduction

It is widely acknowledged, specifically in high-income countries, that a minority of young adult offenders are responsible for the large majority of violent crimes (Falk et al. 2014; Farrington et al. 2006; Laub 2004; Snyder and Sickmund 2006). A vast literature has been amassed on the identification of juvenile offenders at risk to become persistent violent offenders (Baglivio et al. 2014; Hein et al. 2017). Early onset of antisocial or criminal behavior (Moffitt 1993), specifically before the age of 12 (DeLisi and Piquero 2011; Loeber and Farrington 2011), involvement in delinquency and drug use (Lipsey and Derzon 1998), negative or antisocial attitude and the accumulation of criminogenic factors, particularly over multiple domains (Baglivio et al. 2014), have been singled out as key determinants of persistence and escalation of criminal behavior into early adulthood.

However, not all juvenile delinquents who match this profile will develop persistent and violent criminal behavior. Even within high-risk groups there are those who desist from crime before or during the transition from adolescence into adulthood (Bushway et al. 2003; Farrington et al. 2009; Ttofi et al. 2016). From a harm reduction and public safety perspective, this constitutes a need to further differentiate within high-risk target groups for the timely identification of juvenile delinquents at highest risk to develop into young adult violent offenders. Early identification of those juvenile offenders at highest risk to persist or escalate after transitioning into early adulthood should allow for more personalized, specific and effective interventions.

Traditionally, criminological research focuses on prediction models and its resulting risk-assessment instruments are based on logistic regression or ordinary least

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squares analyses. These analyses primarily identify main effects of predictor variables on a particular outcome. However, regression models are less suited to test how to best combine predictors to obtain optimal predictive accuracy (Stalans et al. 2004). This problem becomes more apparent when the number of predictor variables is high, such as in high-risk groups with multiple risk factors at play. As a consequence, many prediction models tend to assume a 'one size fits all' approach (Ngo et al. 2015) that ignores individual particularities and disregards the possibility that not all subgroups within high-risk target populations share the same set of central risk factors (Steadman et al. 2000).

A focus on combinations, or constellations, of risk factors may better explain future violence than stand-alone criminogenic risk factors (Ahonen et al. 2016; Berk and Bleich 2014; Bushway 2013; Onifade et al. 2008). Classification tree analysis (CTA) seems suited to identify constellations of predictor variables associated with a particular outcome. To maximize predictive accuracy, CTA branches off a sample of cases/individuals (juvenile delinquents) in a stepwise fashion according to shared characteristics (criminogenic risk factors) that together are associated with a certain probability of meeting the outcome variable of interest (violent offending). It is a non-parametric technique that identifies homogeneous subgroups in a sample. CTA ranks predictors according to the strength of their association with the outcome and prunes predictors with only a marginal, but significant, contribution. Supposedly, CTA based models of risk assessment are on par with real-life clinical reasoning in making risk judgments, in which characteristics are evaluated sequentially according to their expected relevance to violence/recidivism (Steadman et al. 2000). Especially within high-risk target groups, CTA seems a viable means to identify those juveniles at highest risk of persistent and escalating criminal behavior. This identification is particularly useful when dynamic risk factors are taken into account because those can be targeted by interventions.

Although not conclusive, single CTA-techniques (e.g., CART, CHAID, Rpart) have performed well in predicting violence/recidivism in relatively small study samples (see Ngo et al. 2015 for an overview) such as psychiatric patients (Monahan et al. 2000; Steadman et al. 2000; Thomas and Leese 2003), violent offenders on probation (Stalans et al. 2004), juvenile sex offenders (Van der Put et al. 2013) and ex-detainees (Yang et al. 2010). As such, the current study utilizes a single classification tree approach among a sample of former high-risk juvenile delinquents to answer the following research question: *From a multitude of youth criminogenic risk factors, which constellations of risk factors are most strongly associated with violent criminal behavior in early adulthood?* In answering this question, this study contributes to the literature on prediction methods for violent crime by using a classification tree method that has not been extensively used for violence prediction.

Method

Study design and sampling procedure

A case–control study was performed that was centered around a Dutch cohort of young adult males born between 1985 and 1993 with a known history of juvenile probation in Amsterdam (n = 2300). Within this cohort of former juvenile delinquents, two groups were distinguished: those who persisted and escalated into committing violent offenses and those who committed no violent offenses and as few as possible nonviolent offenses. Childhood characteristics were compared between these groups to identify determinants of violent offending after transitioning into early adulthood.

Childhood characteristics were extracted from information stored in files from their juvenile probation period. These files contain, amongst others, psychological profiles and descriptions of the situation of the child and his context in the years preceding and during the juvenile probation period. From these files, a set of criminogenic risk factors was systematically extracted (see instruments).

Subjects were assigned to one of the two groups based on their offending information as retrieved from the local police registry. Because police data are stored for a limited number of years, the sampling period in early adulthood was limited both in calendar years (2007–2013) and age (18–27 years). For those born in 1985 (the oldest), follow-up was available for the age period 22–27. For those born in 1993 (the youngest), follow-up was available for their ages 18–19. To minimize misclassifications (i.e. incorrectly identifying someone as nonviolent offender and vice versa), the design of the research population maximized observation time while ensuring a minimum follow-up time of at least 2 years in early adulthood, starting before the age of 23.

The following exclusion criteria were applied. Subjects were excluded if they left Amsterdam within the follow-up period according to the municipal records database (n = 414). Participants were excluded if they could not be matched with the police registry (n = 413). Because the majority of young adults who were not found in the police registry could not be matched due to registration errors in their names and/or dates of birth, absent matches did not indicate those former juvenile delinquents who desisted from crime in early adulthood.

With the end of the observation period as a reference, applying this design yielded a population of 1473 young adult offenders with a known history of juvenile probation and a mean age of 22.5 years ($SD = 2.38$). The distinction between violent and nonviolent offenders was made between those with (n = 733) and without (n = 740) one or more young adult violent offenses in the police registry. No differences between the groups were observed for the number of years of follow-up and the average starting age of follow-up. From this group of 1473 young adult offenders, a study population was sampled. Their juvenile probation files were quantified. For violent offenders, sampling was random. For nonviolent offenders, those with the least nonviolent offenses were prioritized. Not all files were available due to logistic reasons or other reasons (n = 358). Files could be unavailable due to youth care involvement with younger siblings, ongoing juvenile justice procedures and school attendance officers who could consult with the juvenile probation agency up to age 23.

Instruments

The Juvenile Forensic Profile (FPJ) was used to extract information from the files (Brand and Van Heerde 2010). This instrument was originally developed for forensic research using files of juveniles with a PIJ order (Placement in an Institution for Juveniles for mandatory treatment), the most severe measure in the Dutch juvenile justice system. The FPJ has good psychometric properties with an overall inter-rater reliability of r = 0.73 and Kappa = 0.61. Its convergent validity with the SAVRY (structured assessment of violence risk in youth; Meyers and Schmidt (2008), which aims to measure the same construct as the FPJ, is good with Kappa = 0.61. The FPJ also has good predictive validity (AUC = 0.803) (Brand 2005a, b; Van Heerde et al. 2004; Van Heerde and Mulder 2005).

The FPJ consists of around 70 risk factors, arranged in seven domains: history of criminal behavior, upbringing and environment, offense situation and drugs, psychological functions, psychopathology, social and relational, and behavior during stay in the institution. The majority of risk factors are measured on a three point scale with 0 = no risk, 1 = moderate risk and 2 = severe risk. Types of offenses committed during youth (property, violent and sexual offenses), out of home placement and committing under the influence of alcohol/drugs were yes/no measures. The FPJ domain behavior during stay in institution and the items number of (non)violent offenses were omitted due to insufficient information (juvenile probation files are not police or juvenile justice records). Some items were added to score information about the household composition, if offenses during youth were mainly committed alone or in a group and parental somatic problems. Table 2 presents all risk factors included in the study.

Scoring of childhood criminogenic risk factors

Two raters were trained in extracting information on risk factors from juvenile probation files. With these two trained raters supervising, a set of practice files was scored by six raters independently. After the threshold of 80% consensus in administered scores on these practice files was reached, files were allocated to single raters and every tenth file was scored by multiple raters. In a 1 year data-collection period as many files as possible were scored. Scoring of a typical file took 4 h on average, raters could score two files in a day.

Sample

In a 1-year data collection period, 387 from 1115 available files were quantified (34.7%). This sample consisted of 146 violent offenders (37.7%; base rate $P_{violence} = .38$) and 241 nonviolent offenders (62.3%). On average, violent offenders had as young adults committed 16.4 ($SD = 14.0$) offenses of which 3.3 ($SD = 2.00$) were violent. Nonviolent offenders had on average committed 2.0 ($SD = 1.3$) exclusively nonviolent offenses (see Table 1).

Inter-rater reliability

Based on 42 multiple scored files that yielded a pool of 148 score forms, inter-rater reliability (IRR) measures were calculated. IRR was satisfactory with R = 0.79 ($p < .001$), ICC = 0.77 ($CI_{95\%}$ 0.75–0.80, $p < .001$) and Kappa = 0.67 ($p < .001$). The proportion of raw agreement was 81.9%, of deviating scores between raters by one point was 16.5% and of deviation by two points was 1.6% (i.e. no vs. severe risk). The raw correlation (R) and intra-class correlation coefficients (ICC) were very strong (Cicchetti 1994). Kappa was substantial according to the Landis and Koch classification (Landis and Koch 1977).

Analysis

Analyses were performed with the SPSS 21.0 statistical package. Chi square tests and one-way ANOVAs identified univariate differences between violent and nonviolent offenders on sociodemographic characteristics and all FPJ items. Chi square Automatic Interaction Detection (CHAID) analysis was performed to identify constellations of risk factors associated with violent offending. CHAID analysis is a classification tree analysis (CTA) to identify the most important explanatory variables for an outcome measure.

The analysis starts with the total sample in a "root node". Continuous variables are transformed into categorical variables. Except for dichotomous predictors, the algorithm explores which pair of scores (categories) is least significant with respect to the outcome. This pair is merged. This step is repeated to find the next pair of

Table 1 Overview of the mean number of (violent) offenses committed during early adulthood and specific type of offenses committed at least once by young adult violent and nonviolent offenders

	Violent offenders (n = 146)			Nonviolent offenders (n = 241)		
	Range	**M**	**SD**	**Range**	**M**	**SD**
Total number of offenses committed	3–96	16.38	12.40	1–5	2.00	1.32
Violent offenses committed	1–11	3.34	2.00	–	–	–
Types of offenses committed at least once	***n***	**%**		***n***	**%**	
Property crime no violence	119	81.5		67	27.8	
Violent property crime	101	76.0		–	–	
Violent offense	115	78.8		–	–	
Drug related offense	40	27.4		20	8.3	
Weapon related offense	38	26.0		4	1.7	
Sexual offense[a]	4	2.7		2	.8	
Traffic offense	90	61.6		44	18.3	
General offenses public domain	78	53.4		24	10.0	
Arson	3	2.1		4	1.7	
Other[b]	113	77.4		116	48.1	

[a] Sexual offenses concerned sexual harassment, not rape or sexual assault which would be considered violent crimes

[b] Examples of the most common other offenses were insulting a police officer, not following police orders, public intoxication, resisting arrest, violation of judicial terms, false identity, vandalism and trespassing

categories. For dichotomous outcome variables, CHAID uses the Chi square test to identify the predictor variable that, with respect to the outcome, most significantly splits the root node into two or more homogeneous groups according to this predictor's categories. The same steps are then applied for the subgroups, creating more branches within the sample. This recursive partitioning ends when no further splits improve within-partition homogeneity, or when a predetermined maximum tree-depth is reached. The final partitions are referred to as leaves, end nodes or terminal nodes, in which cases with the same scores on risk factors are grouped together. These terminal nodes represent higher-order interactions between predictor variables unlikely to have been discovered with regression analyses (Berk and Bleich 2014).

All statistically significant univariable differences ($p < .05$) between the two groups were included as predictor variables. The minimum number of cases in terminal-nodes was 20 (5% of the sample) and the significance level of $p < .05$ for splitting nodes was applied. Missing values were treated as valid scores and are represented in the final tree. A misclassification risk of the final tree was estimated using cross validation with tenfolds.

$P_{violence}$ indicates the proportion of violent offenders within a node. Each endnode's $P_{violence}$ was set against the base rate of violent offending in the overall sample to distinguish between low and high risk of violent offending. A $P_{violence}$ twice the base rate was defined as high risk and a $P_{violence}$ twice as low the base rate was defined as low risk.

Results

In 2013, at the end of the observation period, the mean age of all sampled offenders was 22.1 ($SD = 2.1$) and the mean observation time was 3.86 years ($SD = 1.43$). Although the design of the cohort and sample allowed for differences in ages at the start/end of the observation time, no differences between violent and nonviolent offenders regarding age and available observation time were observed. Ethnic composition of both groups differed ($\chi^2 = 29.7$, $p < .001$). In comparison with nonviolent offenders, nearly twice as many violent offenders had a North African migrant background (44.7% vs. 21.9%) and fewer had a native Dutch background (9.9% vs. 27.8%). Also, fewer violent offenders grew up with a foster parent (26.6% vs. 42.9%, $\chi^2 = 8.0$, $p < .01$), violent offenders had on average more siblings (3.32 vs. 2.32, $t = -4.41$, $p < .001$) and more violent offenders had an older brother(s) than nonviolent offenders (53.8% vs. 36.3%, $\chi^2 = 6.68$, $p < .01$)

(not in table). With respect to other FPJ items,[1] violent offenders were higher on risk on 28 of 63 FPJ items. This concerned, amongst others, 5 items from the 'history of criminal behavior' domain. For example, 98.6% of violent offenders had already as a juvenile committed a violent crime and 74.2% of the nonviolent offenders (Table 2). Nonviolent offenders were higher on risk on the FPJ item presenting with symptoms of depression only (see Table 2).

CHAID analysis

The CHAID analysis yielded a decision tree with three levels (Fig. 1 and Table 3). From 5 sociodemographic characteristics and 29 FPJ-items that were found significantly different between the two groups, 6 factors were identified as (most) significant segmenting variables: *involvement with criminal peers*, *offenses under the influence of drugs*, *offenses under the influence of alcohol*, *criminal family members*, (symptoms of) *depressive disorder* and *dysfunctional family*. Cross validation of the model yielded a misclassification risk estimate of .24. The analysis correctly predicted 78% of all cases. The model had a sensitivity of 93% and a specificity of 55%. The AUC was .86 ($CI_{95\%}$ .82–.90).

Chi squared tests identified *involvement with criminal peers* as most significant segmenting variable (i.e. $\chi^2 = 107.3$, $p < .001$) that divided the root node into three child nodes according to the level of severity of the risk factor (*no/missing* vs. *moderate* vs. *severe*). These nodes further branched into 8 endnodes (see Fig. 1 and Table 3). Additionally to Fig. 1, Table 3 also presents the distribution of missing values within each of the endnodes.

Nodes associated with a high probability of violent offending were endnodes 9 and 13. As juveniles, offenders in node 9 were *severely involved with criminal peers* and had *moderate/severe criminal family members*. Node 9 consisted of 69 offenders (18% of sample) and was associated with $P_{violence} = .80$. Offenders in node 13 were *moderately involved with criminal peers*, had committed *offenses under the influence of drugs*, or this was unknown, and had a *moderate/severe dysfunctional family*. Node 13 consisted of 29 offenders (8% of sample) and was associated with $P_{violence} = .86$.

Endnodes 4 and 11 were associated with a low risk of violent offending. Endnode 4 consisted of 96 offenders (25% of sample) who as juveniles were *not involved with criminal peers* and had *not committed offenses under the influence of alcohol*. Two offenders in this node were violent offenders during early adulthood ($P_{violence} = 0.02$). Endnode 11 consisted of 38 offenders (10% of total sample) who as juveniles were *moderately involved with criminal peers*, had *not committed offenses under the influence* of drugs and presented with *moderate/severe (symptoms of) depressive disorder*. One offender in this node was a violent offender during early adulthood ($P_{violence} = 0.04$).

Discussion

This study aimed to identify constellations of childhood risk factors most strongly associated with violent criminal behavior in early adulthood in a sample of former high-risk male juvenile delinquents. Eight constellations of childhood risk factors were recognized, of which two were associated with the highest risk of violent offending. The first consisted of offenders who as juveniles had been moderately involved with criminal peers, who had committed offenses under the influence of drugs, and who had grown up in a dysfunctional family. The second was characterized by severe involvement with criminal peers and having criminal family members in childhood. Having presented with (symptoms of) depressive disorder as a juvenile was associated with a lower risk of violent offending.

The sample was drawn from a larger population of young adult male offenders with a history of juvenile probation. Within an average observation time of nearly 4 years during early adulthood, half of all offenders were violent offenders. They were recognized in the police registry on account of at least one violent crime committed in early adulthood. Besides the dichotomy of violent and nonviolent offending, violent offenders had on average also committed eight times more offenses than nonviolent offenders.

The sample was segmented into eight constellations marked by the presence and/or severity of specific childhood risk factors. These constellations represent higher-order interactions between predictor variables that most likely would not have been detected with logistic regression analysis. Together, the constellations constituted a model that predicted violent offending well. From 34 childhood risk factors that differed significantly in terms of prevalence and/or severity between violent and nonviolent offenders, six were in one or the other combination most strongly associated with violent offending. Five converge with the 'central eight' criminogenic needs

[1] Information based on which FPJ-items were scored was extracted from offenders' juvenile probation files. On average, offenders were 13.98 years old ($SD = 2.71$; range 1.44–17.04 years) when they first came in contact with the youth care system. Those who had been < 12 years old during their initial contact with the youth care system had received youth protection first which, in our sample, was always followed by juvenile probation. Offenders had been under guidance of youth care/juvenile probation for a total time of 3.66 years ($SD = 3.17$), on average. At entry in the youth care system, (family) anamnesis is a standard intake procedure. Additionally, many offenders had been subjected to psychiatric/psychological inquiry and screenings, in which extensive (family) anamnesis is also standard. These anamneses provided information about circumstances and (adverse) events in early childhood, also for those juveniles who had entered the youth care system after 12 years of age. To summarize, a cumulative measure of the risk factors that were present somewhere during their childhood years is provided at the average age of closing the file (13.98 + 3.66 = 17.64 years).

Table 2 Prevalence and severity of youth criminogenic risk factors among violent offenders and nonviolent offenders

Domain 1. history of criminal behavior	Min–max	Violent offenders (n = 146)					Nonviolent offenders (n = 241)					χ2	p
		n	% none	% moderate	% severe	n missing	n	% none	% moderate	% severe	n missing		
Property offense, ever	0–1	143	2.8	n/a	97.2	3	240	25.8	n/a	74.2	1	38.16	< .001
Violent offense, ever	0–1	142	1.4	n/a	98.6	4	240	25.8	n/a	74.2	1	57.75	< .001
Sexual offense, ever	0–1	142	88.7	n/a	11.3	4	238	95.8	n/a	4.2	3	15.05	.002
Arson, ever	0–1	145	86.9	n/a	13.1	1	239	92.5	n/a	7.5	2	2.61	.106
Offenses: mainly solo (0) or in a group (1)	0–1	124	21.8	n/a	78.2	26	223	37.2	n/a	62.8	17	8.08	.004
	Min–max	**n**			**Mean (*sd*)**	**n missing**	**Min–max**	**n**	**Mean (*sd*)**		**n missing**	***F***	***p***
Age of first nonviolent offense	6–17	135			12.8 (*2.25*)	11	7–17	187	13.6 (*1.98*)		54	10.47	.001
Age of first violent behavior	4–19	128			13.8 (*2.55*)	18	6–18	168	14.1 (*2.00*)		63	.90	.343
Domain 2. Upbringing and environment	**Min–max**	**n**	**% none**	**% moderate**	**% severe**	**n missing**	**n**	**% none**	**% moderate**	**% severe**	**n missing**	***χ2***	***p***
Out of home placement (due to self)	0–1	145	77.2	n/a	22.8	1	241	77.2	n/a	22.8	–	.00	1.000
Out of home placement (due to parents)	0–1	145	89.7	n/a	10.3	1	241	92.5	n/a	7.5	–	.96	.328
Early age of onset of problem behavior	0–2	144	0.0	53.5	46.5	2	240	4.2	65.8	30.0	1	15.04	.001
Availability and accessibility of parents	0–2	145	30.3	46.2	23.4	1	235	28.5	53.6	17.9	6	2.47	.291
Adoption problems	0–2	146	97.3	2.1	0.7	–	240	94.6	5.0	0.4	1	2.42	.299
Peer rejection	0–2	136	68.4	24.3	7.4	10	212	67.9	25.5	6.6	29	.19	.943
(inconsistent) Parenting skills	0–2	140	5.7	35.0	59.3	6	227	15.0	42.3	42.7	14	12.50	.002
Authority problems	0–2	143	11.9	41.3	46.9	3	228	18.4	45.6	36.0	13	5.39	.068
Involvement with criminal peers	0–2	143	2.8	42.7	54.5	3	218	40.4	42.2	17.4	23	84.85	< .001
Criminal family members	0–2	137	32.1	13.9	54.0	9	216	68.1	11.1	20.8	25	47.91	< .001
Physical abuse by parents	0–2	127	53.5	22.8	23.6	19	206	55.8	22.3	21.8	35	.19	.908
Physical abuse by others	0–2	141	82.3	13.5	4.3	5	234	73.9	19.2	6.8	7	3.50	.174
Neglect	0–2	137	64.2	24.1	11.7	9	226	72.6	19.9	7.5	15	3.17	.205
Sexual abuse by parents	0–2	142	100.0	–	–	4	237	99.2	–	0.8	4	.13	.715
Sexual abuse by others	0–2	142	95.8	2.8	1.4	4	237	97.5	0.8	1.7	4	2.17	.339
Domestic violence	0–2	112	58.9	15.2	25.9	36	200	66.0	8.5	25.5	41	3.51	.173
History of prior youth care	0–2	145	3.4	15.9	80.7	1	241	5.4	17.0	77.6	–	.92	.632
Dysfunctional family (disrupted hierarchy)	0–2	140	50.0	25.0	25.0	6	222	74.3	13.1	12.6	19	22.32	< .001
Escalating family situations	0–2	132	81.1	11.4	7.6	14	228	81.6	12.3	6.1	13	.32	.852
Truancy/school drop-out	0–2	141	15.6	24.1	60.3	5	234	13.7	19.7	66.7	7	1.60	.449
Parental substance abuse	0–2	133	78.9	6.0	15.0	13	212	69.8	11.3	18.9	29	4.10	.129
Parental mental health problems	0–2	124	77.4	12.9	9.7	22	207	70.0	16.4	13.5	34	2.17	.339
Parental somatic problems	0–1	114	52.6	n/a	47.4	32	217	71.9	n/a	28.1	24	11.39	.001
Learning problems	0–2	139	71.2	24.5	4.3	7	219	75.8	19.6	4.6	22	1.16	.560

Table 2 (continued)

Domain 2. Upbringing and environment	Min–max	n	% none	% moderate	% severe	n missing	n	% none	% moderate	% severe	n missing	χ2	p
Threat to end up in prostitution	0–2	146	98.6	1.4	–	–	238	99.6	0.4	–	3	.18	.67
Avoiding supervision/escape	0–2	145	17.2	77.2	5.5	1	235	40.9	57.9	1.3	6	26.42	< .001
Domain 3. Offense situation and drugs	**Min–max**	**n**	**% none**	**% moderate**	**% severe**	**n missing**	**n**	**% none**	**% moderate**	**% severe**	**n missing**	***χ2***	***p***
During medicine abstinence/psychosis	0–2	143	98.6	0.7	0.7	3	238	100.0	–	–	3	3.94	.140
Under influence of alcohol	0–1	100	62.0	n/a	38.0	46	218	87.2	n/a	12.8	23	24.87	< .001
Under influence of drugs	0–1	71	63.4	n/a	36.6	75	204	90.7	n/a	9.3	37	26.73	< .001
Against familiar person	0–2	140	67.1	25.0	7.9	6	238	79.0	13.0	8.0	3	8.90	.012
Sexually related, in search of a victim	0–2	146	99.3	0.7	–	1	240	100.0	–	–	1	.06	.801
Domain 4. Psychological functions	**Min–max**	**n**	**% none**	**% moderate**	**% severe**	**n missing**	**n**	**% none**	**% moderate**	**% severe**	**n missing**	***χ2***	***p***
Lack of empathy	0–2	130	9.2	60.0	30.8	16	196	46.4	36.2	17.3	45	50.10	< .001
Impaired conscience development	0–2	134	0.7	56.0	43.3	12	203	18.2	65.0	16.7	38	43.77	< .001
Ego-strength/susceptible (to peers)	0–2	139	12.9	57.6	29.5	7	183	16.9	57.4	25.7	58	1.25	.536
Low impulse control	0–2	131	11.5	38.2	50.4	15	208	22.6	49.5	27.9	43	18.88	< .001
Lack of problem awareness/problem insight	0–2	133	2.3	48.1	49.6	13	213	28.2	46.5	25.4	28	44.15	< .001
	Min–max	**n**	**Mean (*sd*)**			**n missing**	**n**	**Min–max**	**Mean (*sd*)**		**n missing**	***F***	***p***
Total IQ	54–121	96	82.4 (*13.8*)			50	131	51–129	87.2 (*13.5*)		110	6.93	.009
Domain 5. Psychopathology	**Min–max**	**n**	**% none**	**% moderate**	**% severe**	**n missing**	**n**	**% none**	**% moderate**	**% severe**	**n missing**	***χ2***	***p***
Addiction problems: *gambling*	0–2	128	98.4	0.8	0.8	18	229	98.3	1.3	0.4	12	.38	.825
Addiction problems: *alcohol*	0–2	127	66.9	27.6	5.5	19	219	76.3	19.2	4.6	22	3.64	.162
Addiction problems: *drugs*	0–2	134	26.1	61.2	12.7	13	216	40.3	46.8	13.0	25	8.06	.018
ADHD/hyperactivity	0–2	141	75.9	16.3	7.8	5	222	86.5	7.2	6.3	19	8.11	.017
Anxiety disorder	0–2	138	93.5	5.1	1.4	8	233	92.7	5.6	1.7	8	.09	.958
Depressive disorder	0–2	136	85.3	14.0	0.7	10	222	74.8	18.0	7.2	19	9.46	.009
Neurological problems	0–2	135	97.0	3.0	–	11	225	96.0	3.6	0.4	16	1.04	.595
Development personality disorder type B	0–2	108	25.0	28.7	46.3	48	201	57.2	27.9	14.9	40	42.59	< .001
Feelings of hostility/agressiveness	0–2	142	97.2	2.8	–	4	232	98.7	0.9	0.4	9	3.00	.224
Autism spectrum disorder	0–2	144	97.2	2.1	0.7	2	233	94.8	2.6	2.6	8	2.10	.350
Psychotic symptoms	0–2	142	95.8	3.5	0.7	4	235	96.6	1.3	2.1	6	3.29	.193
Sadism	0–2	146	94.5	5.5	–	2	237	98.7	0.8	0.4	4	8.47	.014

Table 2 (continued)

Domain 5. Psychopathology	Min–max	n	% none	% moderate	% severe	n missing	n	% none	% moderate	% severe	n missing	χ2	p
Sexually deviant behavior	0–2	143	88.8	8.4	2.8	3	227	95.6	3.1	1.3	14	6.26	.044
Pedosexual behavior	0–2	146	98.6	1.4	–	–	238	100.0	–	–	3	1.17	.280
Domain 6. Social and relational	**Min–max**	**n**	**% none**	**% moderate**	**% severe**	**n missing**	**n**	**% none**	**% moderate**	**% severe**	**n missing**	**χ2**	***p***
Negative affect/attitude	0–2	140	42.9	40.7	16.4	6	225	66.7	25.8	7.6	16	20.81	< .001
Emotional support	0–2	136	64.7	33.1	2.2	10	233	70.8	24.0	5.2	8	5.00	.082
Total social network	0–2	142	12.0	78.9	9.2	4	234	45.3	50.4	4.3	7	45.14	< .001
Secundary social network	0–2	140	2.1	57.1	40.7	6	235	28.1	51.1	20.9	6	44.94	< .001
Social skills	0–2	136	47.8	37.5	14.7	10	217	59.0	32.7	8.3	24	5.66	.049

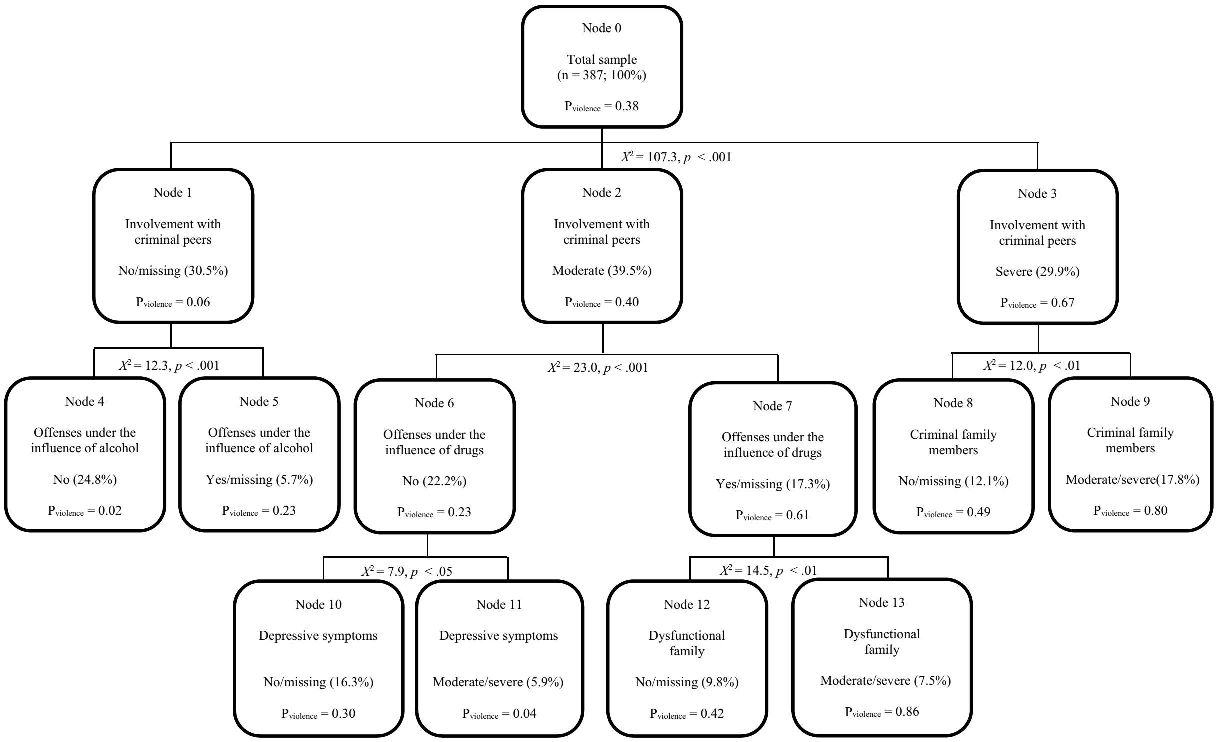

Fig. 1 Graphical display of the results from the CHAID analysis with P$_{violence}$ (violent criminal behavior) as dependent variable. $P_{violence}$ estimates associated with the end nodes only have value as prevalence estimates of violent criminal behavior in comparison with each other

Table 3 Results from the CHAID analysis with violent criminal behavior as dependent variable

End-node	Criminogenic factors	Score	*n*	%	$P_{violence}$
4	Involvement with criminal peers	No/missing	75/21	24.8	.02
	Offense under the influence of alcohol	No	96		
5	Involvement with criminal peers	No/missing	17/5	5.7	.23
	Offense under the influence of alcohol	Yes/missing	11/11		
10	Involvement with criminal peers	Moderate	63	16.3	.30
	Offense under the influence of drugs	No	63		
	Depressive symptoms	No/missing	61/2		
11	Involvement with criminal peers	Moderate	23	5.9	.04
	Offense under the influence of drugs	No	23		
	Depressive symptoms	Moderate/severe	16/7		
12	Involvement with criminal peers	Moderate	38	9.8	.42
	Offense under the influence of drugs	Yes/missing	10/28		
	Dysfunctional family	No/missing	31/7		
13	Involvement with criminal peers	Moderate	29	7.5	.86
	Offense under the influence of drugs	Yes/missing	8/21		
	Dysfunctional family	Moderate/severe	15/14		
8	Involvement with criminal peers	Severe	47	12.1	.49
	Criminal family members	No/missing	38/9		
9	Involvement with criminal peers	Severe	69	17.8	.80
	Criminal family members	Moderate/severe	12/57		
		Total	387	100.0	.38

$P_{violence}$ estimates associated with the end nodes only have value as prevalence estimates of violent criminal behavior in comparison with each other known from the literature (Andrews and Bonta 2010). These were involvement with criminal/antisocial peers (Fergusson et al. 2007; Harder et al. 2015), having committed under the influence of alcohol/drugs (Bonta and Andrews 2007), having criminal family members (Geller et al. 2009; Murray and Farrington 2008) and growing up in a dysfunctional family (Chambers et al. 2001; Gorman-Smith et al. 1998).

Set against the base rate of violent offending in early adulthood (38%), that should be interpreted as a sampling result, two of eight constellations of childhood risk factors were associated with a high risk of violent offending. Together, these comprised 25.3% of the total sample. The first, characterized by moderate involvement with criminal peers and having committed offenses under the influence of drugs (including unknown) and growing up in a dysfunctional family, had a 86% probability of violent offending. Using the FPJ, the risk factor dysfunctional family was assessed based on specific indicators mentioned in their juvenile probation files, among which: severe conflicts between siblings, chaotic household, bad/unhealthy nutrition, parentification, disrupted child-parent hierarchy and stranger in the role of head of the family. Based on these indicators, the risk factor dysfunctional family corresponds with the 'adverse childhood experiences' construct (ACE; Felitti et al. 1998), specifically to its constituent categories parental mental health problems, parental substance abuse, and household violence. Concerning the offenders in this constellation, it could be hypothesized that their ability to form secure attachments to others and the attribution of benevolent motives to others had corroded (Murphy et al. 2014). Drug use, at least occasionally, may have lowered their threshold to engage in criminal behavior (Andrews and Bonta 2010) and the use of violence possibly serves as a means of self-preservation (Polaschek et al. 2009). For juvenile delinquents who do not strongly affiliate with criminal peers, growing up in a dysfunctional family and offending under the influence of drugs were distinctive for developing young adult violent criminal behavior. For diversion efforts to be effective, the early lives of these offenders should not be ignored. Purely 'offense specific' interventions seem unsuited (Perez et al. 2018; Reavis et al. 2013).

The second high-risk constellation, marked by severe involvement with antisocial/criminal peers and having criminal family members, had a 80% probability of violent offending. Besides the influence of criminal members in their social network, no individual risk-factors were present in this high-risk constellation. This suggests that this constellation reflects social learning mechanisms that are well known from the criminological literature, particularly from research into the intergenerational transference of criminal behavior (Farrington 2002) and to a lesser extent also of violent crime (Besemer et al. 2017; Eichelsheim and van de Weijer 2018). From a clinical perspective this is a particularly tough target group because diversion by influencing social networks of marginalized delinquents is notoriously difficult.

Although not one of the central eight criminogenic risk factors, presenting with symptoms of depressive disorder was prominent in our model given its presence in two constellations with a low risk of violent offending. One of those constellations is noteworthy. It consisted of young adults who, as juveniles, had been moderately involved with criminal peers, who had not committed offenses under the influence of drugs and who had presented with depressive symptoms. Strikingly, violent offending in this constellation was much less prevalent than in the neighboring constellation (Fig. 1, node 10) that shared all risk factors except depressive disorder.

Although this effect of depressive (i.e. mood) disorders has previously been observed (Arseneault et al. 2000; Colins et al. 2010; Vermeiren et al. 2002), its exact relation with violent crime remains unclear. For example, a history of depression has been associated with less subsequent antisocial behavior, but only among boys (Oakley et al. 2009). Mood disorders in adolescence have been demonstrated to lower the probability of violent offending specifically (Oakley et al. 2009). This seems in line with our results, albeit that this effect has also been observed for other types of offending (Bevc et al. 2003). Besides observations, explanations have been proposed also. It has been theorized that depressive disorder should be more common among adolescence-limited than life-course persistent offenders, because depressive symptoms are a manifestation of having the inner potential to more strongly experience emotions such as guilt and shame (Vermeiren et al. 2002). Another explanation is that offenders with symptoms of depressive disorder are less prone to violence due to physical inactivity and low energy/fatigue associated with depression (American Psychiatric Association 2000). However, the exact relation between depressive disorder and physical inactivity, especially among adolescents, is unclear (Stavrakakis et al. 2012). Nevertheless, depressive disorder in childhood is associated with other negative outcomes in later life, among which psychopathology (McLeod et al. 2016; Thapar et al. 2012), and social problems (Copeland et al. 2015). As such, active, timely and responsive transference of juveniles with symptoms of depressive disorder and who age out of the juvenile justice/youth care system to adult services is warranted.

Other salient risk factors that were not part of the final model but differed between violent and nonviolent offenders also offer clues to the prediction of violent offending and may guide additional research initiatives. Although it is beyond scope to discuss all of these here, lack of empathy, impaired conscience development, development towards a personality disorder type B (i.e. antisocial) and negative affect were prominently associated with violent offending. These risk factors correspond with callous-unemotional traits (lack of guilt, absence of empathy and callous use of others), that mark subgroups of juvenile offenders with more severe and stable patterns of criminal behavior (Frick and White 2008) and which are important in the development of persistent and escalating criminal behavior (Carlson et al. 2015; Frick et al. 2014).

Strengths and weaknesses

Based on historical information stored in juvenile probation files we systematically retrieved the presence and severity of a comprehensive set of childhood risk factors. A high inter-rater reliability was attained by using a reliable and valid instrument and a group of well-trained raters. Objective police registry data offered a time window of nearly 4 years during early adulthood within which criminal behavior could be observed.

In composing the population from which violent and nonviolent offenders were sampled, a trade-off was made between utilizing as much observation time as possible (to detect violent offenses), minimizing variety in observation time and including as many participants as possible. Nevertheless, differences in observation times between participants could not be avoided. In a case–control design, this increases the likelihood of incorrectly classifying true cases as controls. However, a mean observation time of nearly 4 years was achieved that greatly exceeded the minimum observation time of 2 years. Importantly, no differences in observation time and starting age at follow-up were observed between sampled violent and nonviolent offenders. Also, these groups contrasted sharply with respect to both young adult offending behavior and a multitude of risk factors which suggests validity in our approach.

In our sample, violence went hand in hand with prolificness. As such, apart from the violence element, differences between both groups might also be driven by differences in prolificness. Controlling for overall differences in levels of criminal activity was not possible because separating prolificness from violence would yield too few 'non-prolific but violent' offenders to be able to perform our analyses. Put differently, correcting for prolificness would imply the elimination of violence as the primary outcome.

With a decision tree approach we identified two constellations of risk factors associated with a high risk of violent offending embedded in a model with good predictive accuracy. An important benefit of decision tree models over multiple regression models is that it provides a visualization of characteristics associated with an outcome that is easy to explain and intuitive to understand. Additionally, decision trees can reveal interactions between risk factors that are easily overlooked (Thomas and Leese 2003). As such, it provides a useful means to generate hypotheses about interacting variables associated with violent criminal behavior (Steadman et al. 2000). We consider our model's good predictive accuracy a promising result, given the combination of a relatively small sample and many predictor variables included in the analysis. However, its specificity (55%) was less convincing. An implication of applying our model would be that a group of juvenile delinquents may receive more diversion efforts than needed regarding the prevention of violent offending. This might seem a lesser problem than the opposite situation where too few preventive efforts would be deployed for those who actually do need it. However, from the risk-need-responsivity model (Andrews and Bonta 2010) we know that any mismatch between the intensity of an intervention and the risk of violence/recidivism can yield opposite effects (Andrews 1995; Lowenkamp and Latessa 2005).

Of course, CHAID has some weaknesses. A disadvantage of classification trees in general is the volatility of their outcomes. Small changes in input information may lead to large changes in the tree it constructs. Also, chance interactions can take up a prominent place in the decision tree it produces and not all possible trees are examined. Together, these weaknesses of CHAID influence the generalizability of its results and, consequently, the utility of the models it finds (Thomas and Leese 2003). Random forests (Breiman 2001), an elaboration on CTA, was developed to stabilize decision trees. Random forests (RF) is an algorithm that randomly selects sets of predictor variables from a larger pool of variables to build hundreds of individual decision trees that are averaged in a single outcome tree (Ritter 2013). RF has been shown to outperform logistic regression in risk prediction (Berk and Bleich 2014; Bushway 2013) when applied to large actuarial databases. Nonetheless, RF has the disadvantage of being a 'black box' to the end user (Zeng et al. 2017). Although its input and output can be seen, their users are blind to how one's risk estimate is derived. Additionally, RF is difficult to implement well (Bushway 2013) and there are ethical dilemma's around the use of computer algorithms such as RF as predictive tools to guide criminal justice decisions (Chan and Bennett Moses 2016).

From a variety of single classification tree approaches, the Rpart algorithm in R for recursive partitioning (Therneau and Atkinson 2006) is a more contemporary technique than CHAID. Two features of Rpart made it less suited to our data, however. The first is that Rpart allows for binary splits only, whereas most of our predictor variables had three levels. Second, for cases with a missing value on a splitting variable, Rpart uses the 'best' surrogate variable (e.g., bodyweight for body length) to be able to classify cases to the next node. In contrast, CHAID treats missing values as a discrete category that may or may be not merged with other score categories, which more closely resembles daily practice. Beyond the decision tree approach, latent class analysis (LCA) was an alternative analytical strategy to identify combinations of risk factors associated with violent criminal behavior. LCA was unsuited to our data, however, given the high number of variables with missing values (Table 2) in combination with the default option of LCA to eliminate cases with 1 or more missing values. Imputation of missing values was unsuited as a fallback strategy, because other variables provided insufficient substantive support with respect to variables that required imputation. A traditional classification tree as we used is well suited for dealing with missing values, as was frequently the case in our data.

Our results should be validated before making claims about its generalizability. Important to note is that the $P_{violence}$ estimates of the constellations in our model are not to be generalized to juvenile offender populations. They only have a relative value as prevalence estimates of violent offending in comparison with each other, because the base rate of violent offending was a result of our sampling procedure. To validate our findings it would be preferable to perform a decision tree approach in a prospective cohort study. Nonetheless, five of the six risk factors in our model trace back to the central eight criminogenic needs known from the literature (Andrews and Bonta 2010). Noteworthy, our model resembles that of Ortega-Campos et al. (2016), who used CHAID analysis to predict recidivist sanctionable antisocial behavior among Spanish juveniles charged in a court case. As did we, Ortega-Campos et al. (2016) found involvement with antisocial peers to be a key segmenting factor, experiencing mental health problems to be associated with a lower, and having criminal family members with a higher probability of recidivism.

Finally, despite being one of CHAID's benefits, missing information adds complexity to the interpretation of our model. The CHAID analysis treated missing scores as valid scores. For each risk factor involved, the analysis explored all possible arrangements to determine under which particular grouping of scores (missing/none/moderate/severe) the strongest predictive power regarding violent offending was observed. That information was used to merge categories and, ultimately, to construct the model. To illustrate, the predictive power of depressive disorder was strongest when those scoring no or missing were grouped together and contrasted with those scoring moderate/severe. Again, the model does reflect reality in which the presence or absence of a risk factor may also be unknown. For certain risk factors, missing information is equally likely to indicate that a problem was simply not observed or that a juvenile probation officer was unable to ascertain its presence at that time. As such, our model mimics reality because juvenile probation officers on occasion can neither affirm nor exclude the presence of a particular risk factor. In this respect, a benefit of decision trees over regression based models is that, for example, juvenile probation workers are not hindered by missing information in estimating one's risk.

Nevertheless, we performed sensitivity analyses with alternating coding strategies for missing values of the two most important risk factors, as based on their associated χ^2's (i.e. involvement with criminal peers and offenses under the influence of drugs) (see Fig. 1). In the original model, missing values on involvement with criminal peers were merged with the *no* category. We first placed missing values in the *moderate* or *severe* involvement with criminal peers category, which remained the most important segmenting variable and χ^2 only slightly decreased. Minor changes were only observed when missing values were considered *moderate*. In another sensitivity analysis, we recoded missing values on offenses under the influence of drugs and offenses under the influence of alcohol as *no*, given frequent missing values on these variables. This resulted in a marginal decline in their χ^2. Taking these observations into consideration, coupled with the resulting segmentation of our model suggests robustness in our approach.

Conclusion

Among a group of former high risk juvenile delinquents, a large set of stand-alone childhood risk factors was reduced in number using CHAID analysis to a more compact and manageable set that constituted a model with sufficient predictive accuracy regarding young adult violent offending. We identified eight constellations of risk factors associated with a certain probability of violent offending. The model comprised, among others, two constellations depicting juvenile delinquents at highest risk of violent offending in early adulthood. Juvenile probation officers should be vigilant on youngsters' involvement with criminal peers, whether or not they commit offenses under the influence of drugs and alcohol, the presence of criminal family members and any indication for growing up in a dysfunctional family. Presenting with symptoms of depressive disorder was associated with a lower probability of violent offending. Our results may be helpful in the selection and allocation of prevention and diversion programs for juvenile probation youth.

Abbreviations
ANOVA: analysis of variance; AUC: area under the curve; CHAID: chi square automatic interaction detection; CTA: classification tree analysis; FPJ: juvenile forensic profile; ICC: intraclass correlation coefficient; IRR: inter-rater reliability; $P_{violence}$: probability of violent criminal behavior in early adulthood; PIJ: order placement in an institution for juveniles for mandatory treatment; RF: random forests.

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Authors' contributions
MS and TF are the principal investigators and obtained funding for the study. MS and TF coordinated the data-collection. MS, together with MW performed the data-analysis. MS drafted the manuscript with important contributions from TF, MW and AP. All authors read and approved the final manuscript.

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Availability of data
Data will not be shared. Many variables in combination with a relatively small research population may expose the identity of participants.

Ethics approval and consent to participate
The Medical Ethics Review Committee of the Academic Medical Center Amsterdan ordered that the Medical Research Involving Human Subject Acts (WMO) does not apply to the study and granted a waiver of consent. The Dutch ministry of Justice and the Dutch council of attorneys general from the Dutch public prosecutor's office approved consultation of the police registry granted permission to retrieve offense information from the registry of the local police on the condition that privacy of participants was guaranteed.

Competing interests
The authors declare that they have no competing interests.

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