Using Machine Learning to Predict the Likelihood of Future Risk-Taking Behavior in
Adolescents

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Abstract

Adolescents show more risk taking behavior than children and adults. Most adolescents do not experience adverse consequences of this increased risk taking behavior. However, excessive risk taking can result in long term adverse consequences. To better target prevention efforts at those adolescents who are at risk for excessive risk taking, these adolescents should be identified early. Here we first test which statistical approach is best suited to predict the likelihood of risk taking behavior. We use data from a large, three wave longitudinal sample with 298 participants between the ages of 8-25 at the first measurement. We compare out-of-sample prediction performance of three different forms of Ordinary Least Squares (OLS) regression models and a Least Absolute Shrinkage and Selection (LASSO) model. Results show that the LASSO model outperforms all three OLS regression models on out-of-sample prediction for prediction of risk taking two years later. Furthermore, we show how LASSO can be used to determine a criterion value of who is at risk for specific future behavior, in this case likelihood of excessive risk taking. This criterion value can be used for early identification of individuals at risk and can provide guidance on decisions about prevention efforts.

Keywords: Machine learning, prediction, adolescence, risk taking

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Adolescence is associated with increases in risk taking behavior (Eaton et al., 2010). Risk taking is expressed in behavior such as increased use of alcohol, risky driving and criminal behavior. Although risk taking increases by 200 to 300% during adolescence, most adolescents go through adolescence without suffering long term consequences of risk taking behavior (Minino, 2010). Furthermore, not all risk taking is bad and risk taking can even have positive effects. Risk taking behavior is for instance positively related to strategic exploratory behavior (Somerville et al., 2017), which is important for adolescents to learn about the environment. However, excessive risk taking behavior can lead to long lasting adverse consequences, for instance in the health domain. To protect adolescents from adverse consequences of risk taking, policies are created that limit adolescent's freedom and exposure to risk. Examples are legislation on alcohol use, age of driving and policies on financial decision making. These policies should balance protection of adolescents and exploration of the environment. Ideally, adolescents would have the freedom to develop and take risks to explore their environment, while at the same time those adolescents who need protection are protected and prevented from taking excessive risks. To better target policy at protecting those individuals who are at risk for excessive risk taking we need to be able to predict future risk taking behavior to identify at those groups of individuals who are at risk for excessive risk taking. The main goal of this study is to identify which variables show the highest predictive power for future risk taking behavior.

Predicting future behavior

Predicting future behavior is challenging. Identification of variables with high predictive power for future behavior requires an out-of-sample approach that takes into account the issue of overidentification and requires an estimation model that is able to identify future risk taking behavior. To test the model performance of prediction of future

risk taking behavior a longitudinal dataset is used in which variables are measured twice with a certain interval of time between the first and second measurement. The objective of the estimation model is to predict risk taking behavior measured at the second timepoint using the information from the first timepoint. To do so the out-of-sample approach requires that the data is divided into a training set and a test set. The estimation model is trained using the training set data and the performance of the model is evaluated based on how well the model predicts the outcomes of the test set (i.e. the out-of-sample model performance). In this study we first compare the out-of-sample performance of two statistical approaches: a conventional ordinary least squares regression model and a Least Absolute Shrinkage and Selection (LASSO) model which is machine learning model that finds its roots in regression.

Ordinary Least Squares (OLS) regression models. The conventional estimation model in social sciences is Ordinary Least Squares (OLS). This method estimates the relation between one or more independent variables and one (or more) dependent variable(s) by minimizing the error sum of squares. One problem with OLS models is that these models tend to overfit the data as the number of to be estimated model parameters approaches the number of data points. Intuitively overfitting means a reduction of the degrees of freedom and when there are no degrees of freedom left, the model simply connects the datapoints. Although an overfitted model perfectly predicts the outcomes of the particular data at hand, the model will predict poorly on new data since the predictive power does not come from the observed variation in the independent variables but is a direct result of the lack of degrees of freedom. To mitigate the problem of overfitting the aim is to fit the most parsimonious model to the data (i.e. the model that explains as much variance as possible by using as few predictors as possible). In an OLS setting, this implies that a set of predictors is selected based on theory or through automated selection. In a theory driven model the researcher decides which predictors are included in the model based on theory and past research. Typically, a researcher decides beforehand which variables will be included and only these variables are measured in a study. Performance of this model is therefore

dependent on the researchers' choice of predictors. Automatic variable selection is independent of the researchers' input and therefore less sensitive to exclusion of important variables in a study. However, automatic fitting procedures (such as for example, stepwise regression) are designed for explanatory purposes and not for predictive purposes, such that this particular model does not necessarily perform optimally out of sample. At the same time, kitchen-sink procedures in which all independent variables enter the estimation model do not suffer from subjective choices of the researcher, but they are prone to overfitting issues.

Machine Learning: LASSO models. Machine learning is a branch within artificial intelligence. The machine learning field develops algorithms designed to be applied to data, primarily concerning itself with tasks of prediction, classification, and clustering or grouping (Athey (2018)). One advantage of machine learning models is that they are optimized for out-of- sample prediction, such that overidentification is automatically addressed and which makes machine learning algorithms ideally suited to identify variables to predict future behavior. Supervised learning techniques have the objective to identify the set of features or covariates (X) to optimally predict the variation in the dependent variable (Y). These techniques are not designed to optimally describe the relationship between the independent and dependent variables, but instead the sole purpose is to optimally predict the variation in the outcome variables.

One machine learning model uses ordinary least squares but penalizes the absolute values of the estimation parameters, and is thus suitable for a performance comparison with the conventional OLS approach. This method is referred to as the Least Absolute Shrinkage and Selection Operator Model (LASSO). The regularization and variable selection is integrated in the LASSO procedure, such that a pre-selection of the independent variables is not required. Instead, all independent are considered, but the inclusion of a penalty function that penalizes the sum of the estimated regression coefficients ensure that redundant variables receive a zero weight. In this way, overfitting is prevented and only a set of independent variables is selected that maximized the explained variance in the outcome

variable(s). The inclusion of the penalty function imposes a bias on the estimated parameters with the objective to gain prediction performance.

The current study

The goal of the current study is to identify which variables are best suitable for prediction of future risk taking behavior. Here we use data from a unique large, longitudinal study. In this study participants aged 8-25 years old, at the first time point, were measured three times with a 2-year interval between measurements. Data were collected on a wide array of measurements targeting different aspects of development. Data is included on pubertal development, hormone levels, genes, cognitive development, emotional development, personality and neural measures of reward sensitivity. The outcome measure that we predict is the Domain Specific Risk Taking Scale (DOSPERT) measured two years and four years after the assessment of the predictor variables. The DOSPERT is a questionnaire measure to assess the likelihood of risk taking behavior (Blankenstein et al., 2021). First, we test which statistical model is best suitable for prediction of future behavior. We compare model performance for two different statistical approaches: OLS models and a machine learning model, a LASSO model. One of the differences in these models is the involvement of the researcher in selecting the variables that are retained in the model. In an OLS model that is purely theory driven, the researcher selects the variables without any automated process. In the LASSO model the variables are selected automatically, without any involvement of the researchers. To compare model performance using automated variable selection we include a OLS model in which we use a stepwise approach to select variables. In this approach, variables are retained in the model when they explain additional variance above the other variables in the model. Lastly, we use a OLS model without variable selection. A common feature of OLS models is that they typically perform well explaining variance within sample, but do not perform well when predicting out-of-sample. Therefore, we expect that the OLS models perform better within sample and that the LASSO model performs best on the out of

sample prediction. After determination of the best model, we use this model to identify variables that can be used to predict future risk taking. Together these analyses identify the best statistical approach to predict future behavior and show which variables can be used to predict future risk taking behavior.

Methods

Participants

Data were collected as part of a large, longitudinal study at Leiden University, The Netherlands, called “Braintime”. Participants provided written informed consent in the case of adults and assent and parent consent in the case of minors. All procedures were approved by the institutional review board at Leiden University, The Netherlands. Data from this study have been published before (Achterberg, Peper, Duijvenvoorde, Mandl, & Crone, 2016; Braams, Van Duijvenvoorde, Peper, & Crone, 2015; Peper, Braams, Blankenstein, Bos, & Crone, 2018; Peper et al., 2013; Peters, Koolschijn, Crone, Duijvenvoorde, & Raijmakers, 2014). At the first time point data were collected from a total of 298 participants, ($M_{\text{age}} = 13.96$, $SD_{\text{age}} = 3.65$, $\text{range}_{\text{age}} = 8.01 - 25.96$). At the second time point, two years later, 286 participants were included ($M_{\text{age}} = 15.80$, $SD_{\text{age}} = 3.54$, $\text{range}_{\text{age}} = 9.93 - 26.62$). At the third time point 274 participants were included ($M_{\text{age}} = 17.88$, $SD_{\text{age}} = 3.65$, $\text{range}_{\text{age}} = 11.94 - 28.72$).

Data and descriptive statistics

Data were included for different domains to cover a wide spectrum of potential predictive variables. We included pubertal development, hormone levels, genetic data, cognitive measures, questionnaires, neural measures of reward sensitivity, subjective measures of reward sensitivity, lab based risk taking measures and real life risk taking measures. The outcome variable used in all models was the Domain Specific Risk Taking (DOSPERT) Questionnaire measured at the second time point (2 years after the first time

point) and third time point (4 years after first time point). A description of these measures is detailed below and descriptive statistics for all measures are included in Table 1.

Pubertal development. Pubertal development was assessed with the Pubertal Development Scale (PDS; Petersen, Crockett, Richards, and Boxer (1988)). The PDS is a self-report questionnaire, comprised of five questions assessing secondary sexual characteristics. Questions are included on growth spurt, body hair, changes in the skin, and for boys a question about change in voice and facial hair and for girls a question about breast development and menarche. Participants indicated on a four-point scale whether a physical characteristic: (1) had not yet started to develop, (2) was showing the first signs of development, (3) was showing clear development, or (4) had already finished developing. The PDS was filled out by participants aged 17 and younger. An average score was calculated and used for analyses (Braams et al., 2015; Wierenga et al., 2018).

Hormones. Morning saliva samples were collected and assayed for testosterone and estradiol. DHEA levels were measured in morning urine samples, collected directly after waking up. Saliva samples were collected by passive drool. Participants collected saliva directly after waking up, and before eating or brushing teeth. Females who had not yet reached menarche and males collected saliva on the day of fMRI testing. Postmenarcheal females and females who used contraceptives with a stopping period collected saliva on the seventh day of their menstrual cycle to control for hormone fluctuations. Females who used contraceptives without a stopping period, such as hormonal intrauterine devices, were excluded from hormone assessment (Braams, Peper, Heide, Peters, & Crone, 2016; Braams et al., 2015; Peper et al., 2018, 2013; Peper, Reus, Heuvel, & Schutter, 2015; Wierenga et al., 2018).

Genes. DNA was collected using a cheek swab. Polymorphisms for the human dopamine transporter gene (DAT1) and catechol-O-methyltransferase (COMT) were determined. Both DAT1 and COMT are dopamine-modulating genes and can have three different polymorphisms: DAT1 9/9, 9/10 and 10/10 and COMT val/val, val/met and

met/met.

Cognitive measures

IQ. An approximation of IQ was determined by two subscales, similarities and block design, of the Wechsler Intelligence Scale for Adults (WAIS-III) or the Wechsler Intelligence Scale for Children (WISC-III). Performance on the similarity subscale was used as a proxy for verbal IQ and performance on the block design subscale was used as a proxy for performal IQ. Both scores combined were used as an approximation of general IQ (Peters et al., 2014; Peters, Van der Meulen, Zanolie, & Crone, 2017).

Working memory. The Mental Counters task was used as a measure for working memory (Huizinga, Dolan, & Molen, 2006; Larson, Merritt, and Williams (1988)]. In this task participants are presented with a screen with two horizontal lines. A square can appear above or below one of these lines. Whenever a square appears above a line the “score” for that line increases by one, when a square appears below the line the “score” for that line decreases by one. Participants are instructed to press a button when one of the lines reaches a certain value, the criterion value. The criterion value changes on each trial. Participants had to respond within 3500 ms once criterion was reached. Performance on this task was defined as proportion correct responses (Peters, Duijvenvoorde, Koolschijn, & Crone, 2016).

Questionnaires

BIS/BAS. The Behavioral Inhibition System/Behavioral Activation System (BIS/BAS) questionnaire is comprised of 24 items assessing four subscales (Carver & White, 1994). One subscale measures punishment sensitivity (BIS), whereas the three other scales each measure a separate aspect of risk taking tendency, i.e. persistence in the pursuit of rewards (BAS Drive), desire for rewards and the willingness to approach these (potential rewards (BAS Fun Seeking) and responses to anticipation and receipt of rewards (BAS Reward Responsiveness) (Becht et al., 2018; Braams et al., 2015; Peper et al., 2018; Schreuders et al., 2018).

Baratt Impulsiveness Scale. The Baratt Impulsiveness Scale (BIS-11) assesses impulsive behavior (Patton, Stanford, & Barratt, 1995). The BIS-11 is comprised of three subscales: motor impulsiveness, non-planning and attentional impulsivity. The total score is a measure of general impulsivity. In the current study we used the total score (Peper et al., 2018; Peper, Mandl, et al., 2013).

Buss Perry Aggression Questionnaire. The Buss Perry Aggression Questionnaire (BPA-Q) was used to assess self-reported aggression (Buss & Perry, 1992). The BPA-Q consists of four subscales: physical aggression, verbal aggression, anger and hostility. Mean scores on each of the subscales were used for analysis. The cumulative score for each of the subscales was divided by the total number of items for each scale to generate these mean scores (Bos et al., 2018; Peper et al., 2018, 2015).

Emotion Awareness Questionnaire. The Emotion Awareness Questionnaire (EAQ) was used to assess emotional awareness (Rieffe et al., 2007). The EAQ is comprised of six subscales assessing differentiating emotions, verbal sharing of emotions, bodily awareness of emotions, acting out emotions, analyses of emotions and attention to others' emotions.

Friendship Quality Scale. Friendship quality with the participants' best friend was assessed using the Friendship Quality Scale (FQS) (Bukowski, Hoza, & Boivin, 1994). The FQS is comprised of 20 items assessing positive as well as negative friendship quality. Higher scores indicate higher friendship quality (Braams & Crone, 2017a; Braams et al., 2014).

NEO Personality Inventory. Three subscales of the NEO Personality Inventory-Revised (NEO-PI-R) were administered: impulsivity, depression and anxiety (De Fruyt, Mervielde, Hoekstra, & Rolland, 2000). The total score on each subscale was used for analysis (Peper et al., 2018; Schutter, Meuwese, Bos, Crone, & Peper, 2017).

Reward sensitivity

Functional MRI. Participants performed a gambling game while inside the MRI scanner. In this game the computer would choose heads or tails and if the participant

correctly predicted the outcome they would win money, if they were wrong they would lose money. The task consisted of two event related runs of approximately seven minutes. Participants played 30 trials for themselves, 30 for their best friend and 30 for a disliked other. In the current analysis we only included data for the trials in which they won or lost money for themselves as these data are an indication of reward sensitivity for self. Data were extracted from an a priori defined cluster of the Nucleus Accumbens (Braams & Crone, 2017b; Braams et al., 2014, 2014, 2016, 2015; Duijvenvoorde, Achterberg, Braams, Peters, & Crone, 2016; Schreuders et al., 2018).

Task ratings. Participants filled out several ratings to indicate their subjective experience during the functional MRI task. Participants rated how much they enjoyed winning and losing for themselves and their best friend. They also rated how much they believed that their friend deserved to win and how much they objectively think their friend deserves to win (Braams et al., 2014).

Lab based risk taking measures

Balloon Analogue Risk Task (BART). The BART was used to assess laboratory risk taking behavior. In this task participants pump up a virtual balloon (Lejuez, Aklin, Zvolensky, & Pedulla, 2003). With each pump the participant earns 5 cents. Participants are free to choose at which point they want to stop inflating the balloon and put the money in the bank. If participants decide to put the money in the bank the task then continues with the next balloon. Money that has been stored in the bank is safe. Balloons can also pop. If the balloon pops the money earned with that balloon is lost and the task continues with the next balloon. In total the task consisted of 30 balloons. We used the mean number of successful pumps and number of balloons popped as outcome variables of this task (Braams et al., 2015; Peper et al., 2018, 2013).

Delay discounting. Delay discounting refers to the concept that money is valued less at a delay and is a measure of impatience. Participants were asked to choose between a

small amount of money that was available immediately or €10 available after a delay. Discounting was assessed at four different delays: 2 days, 30 days, 180 days and 365 days. The indifference point was defined as the amount of money that was chosen equally often as the €10 after each delay. Based on the indifference points at each delay a discounting curve was fitted for each subject. The area under the curve (AUC) of this discounting curve was used as a measure of discounting. The AUC varies between 0 (complete discounting) to 1 (no discounting) (Achterberg et al., 2016; Peper et al., 2018; Peper, Mandl, et al., 2013). We also included the average reaction time as a predictive variable.

Ultimatum Game

The ultimatum game is an experimental economics game in which one party proposes a division of 10 coins which can be accepted or rejected by the other party. If the offer is accepted the coins are divided as proposed, if the offer is rejected neither gets any coins. Participants played the ultimatum game once as player 1, making the division, and once as player 2, accepting or rejecting an offer. Participants were first asked to divide the 10 coins between them and the next participant in the study. They were told that the next participant could accept or reject this offer. After participants made their offer they were told that the last participant in the study also proposed a division of the coins. This division was always an unfair division of 1 coin for the participant and 9 coins for the other person. Participants were asked to accept or reject this offer (see also Braams et al., 2014).

Real life risk taking

Substance use. Participants filled out a questionnaire in which they self-reported the use of alcohol, cigarettes and cannabis. Participants reported how many glasses of alcohol they consumed last week, last month and in total in their lifetime. A glass of alcohol was considered a standard 250 ml, 8.4 oz, glass. Participants were instructed to count bottles and cans as 1.5 glass. Participants reported how many cigarettes they smoked last week (on a scale from 0-90, 0-never 90-more than 90 times) and how often they smoked cannabis in

their lifetime (on a scale from 0-20, 0-never 20-more than 20 times). At the second time point participants were asked to report the age at which they consumed alcohol for the first time, the age that were drunk for the first time, the age that the smoked their first cigarette and cannabis, and the age that they used hard drugs for the first time. Although these measures were collected at the second time point, they were used as predictive variables in the analyses (Braams et al., 2016; Peters, Jolles, Duijvenvoorde, Crone, & Peper, 2015).

Outcome measure

The Domain Specific Risk Taking Scale (DOSPERT) was used as the outcome measure of risk taking behavior (Blankenstein et al., 2021; Weber, Blais, & Betz, 2002). The DOSPERT is a questionnaire which assesses the perceived risk, expected benefits and likelihood of risk-taking behavior. In the current study we only used the self-reported likelihood of risk taking as the outcome measure. Age appropriate versions of the DOSPERT were administered. Participants respond using a 7-point Likert scale. The mean score across all items was calculated and used as the outcome measure. Participants responded to items assessing likelihood of risk taking in five different domains: ethical, financial, health/safety, recreational and social. In the current study we used the total score on all domains as the outcome variable. The DOSPERT was administered at timepoint 2 (T+2 years) and timepoint 3 (T+4 years). DOSPERT data for time point 2 and time point 3 was relatively normally distributed, indicating that our performance measures (see model performance comparison section below for details) for evaluating model prediction performance will not likely be jeopardized by outliers.

Empirical strategy

For all models the potential input variables are all variables described above and the predicted variable was the DOSPERT score. Data were split into a training set (70%) and a test set (30%). The training set was used to fit the models. The test set was used to evaluate out-of-sample prediction model performance. We compare three OLS models and a

LASSO model. In the first OLS model we selected the variables based on past research and theory. In this theory based OLS model we included the following predictors: testosterone level, number of exploded balloons in the BART, the indifference point at 30 days in the delay discounting task, all subscales of the BIS/BAS questionnaire and the age at which a participant reported to be drunk the first time. In the second OLS model we used an automated selection procedure. Here we used a stepwise backward selection procedure. In this procedure all variables are included at the start of the procedure. Variables are deleted one by one after which model fit is evaluated. If model fit is significantly improved after selection of a variable, this variable is retained. The process is repeated until no variables can be selected that improve the model fit. In the third OLS model, we do not select predictors and include all available predictors. This “kitchen sink” approach includes all variables, thereby exploiting all the information that is available, regardless of whether a variable predicts statistically significantly. This approach is included for completeness only as this model bears a high risk of overfitting and degrees of freedom problems. The fourth model is the LASSO estimation model in which the variable selection is performed through regularization. Regularization adds an additional penalty term in the error function such that the optimal functional form is tuned while acknowledging the problem of over-fitting. The sum of the absolute estimation parameters is penalized with λ and thus the model error increases (i.e. the model performance decreases), explaining the name of LASSO: Least Absolute Shrinkage and Selection Operator. Essentially, the regularization process optimizes λ . If the optimal value for λ is 0 then overfitting is no problem, but the higher the optimal value λ , the more estimation parameters are set to zero, thereby eliminating variables from the estimation model with the objective to optimize model performance. An interesting feature of the LASSO model is that as λ increases the bias increases, while as λ decreases the variance increases such that model performance is optimized by choosing an optimal bias-variance trade-off. It follows that the estimation parameters of LASSO can solely be used for prediction purposes, and not for interpreting the (biased) estimation parameters.

Model performance comparisons

In the first set of analyses we fit models to predict DOSPERT scores, which is a continuous outcome measure. Model fit for models to predict continuous outcomes can be evaluated based on R-squared and Root Mean Square Error (RMSE). R-squared is a measure of how much of the variance is explained by the model. R-squared can take values between 0 and 1, with 0 meaning no variance is explained and 1 meaning 100% of the variance is explained. RMSE is the standard deviation of the residuals (i.e. the prediction errors). The lower the residuals, the lower the RMSE and the better the model performance. R-squared is a relative measure of model fit, whereas RMSE is an absolute measure, making R-squared a more intuitive measure to interpret. R-squared is included as it is the most intuitive measure of model fit, however RMSE is the preferred indicator of model fit. Both R-squared and RMSE are calculated in-sample (i.e. training sample), degrees of freedom-adjusted in-sample (to account for over-fitting issues as a result of adding predictor variables when estimating your prediction model) and out-of-sample. Note that df-adjusted measures do not apply to out-of-sample, as the coefficients are not estimated there but rather taken from the in-sample results, so no degrees of freedom are lost out-of-sample. Performance of all models was compared for prediction of behavior two years after the initial assessment and four years after the initial assessment.

Results

Model performance comparisons

We first tested which model best predicts the likelihood of risk taking two years and four years after the initial measurement period. We compared in- and out-of-sample prediction for the four different models, i.e. theory driven OLS, backwards selection OLS, kitchen sink OLS, and LASSO. As expected, in-sample performance, after degrees of freedom adjustment and selected based on RMSE, was highest for the stepwise backward selection OLS model. This model explains 42% of the variance for risk taking behavior two years later

and 27% of the variance four years later, see Table 2. However, the LASSO model showed the best out-of-sample performance. Out of sample prediction was best for risk taking behavior two years after the initial measurement. Compared to the next best model, the theory driven OLS model, the out-of-sample prediction by the LASSO model is improved by 25%, see Table 2. The theory-driven OLS model performed best for the out of sample prediction of risk taking behavior four years after the initial measurement, see Table 2. Although this model performs best in prediction of risk taking four years later, the explained variance is only 13%.

Identification of variables to predict the likelihood of risk taking behavior

The out of sample performance of the LASSO model to predict likelihood of risk taking behavior two years after the initial measurement is the best of all compared models. The model predictors retained in this model are reported in Table 3. These predictors can be measured and used to predict the likelihood of future risk taking behavior.

Using machine learning for prediction of the likelihood of future risk-taking behavior

One of the goals of these analyses is to predict who is at risk for excessive risk taking. In this section we show how LASSO models can be used to define a cut-off point, i.e. criterion value, to decide who to classify as at risk for excessive risk taking. This information can be used to guide decisions on new policies and for instance which individuals to target in a prevention programme. In these models the outcome measure is a dichotomous variable in which the participants are classified as, in this case, excessive risk taker or non-excessive risk taker. To evaluate the model performance of the predicted dichotomous outcomes we focus on three different metrics: accuracy, sensitivity and specificity. Accuracy refers to how well the model classifies all outcomes. In other words, how well can the model identify true positives and true negatives, in this case classify excessive risk-takers and non-excessive risk-takers. No model will be 100% accurate in their classification. Sometimes

a model will identify someone as an excessive risk-taker when this person is in fact not an excessive risk taker (false positive), and vice versa (false negative). If we want to know whether the model overidentifies risk takers or non-risktakers, we can look at the sensitivity and the specificity. The sensitivity refers to classification of true positives, i.e. how many of the excessive risk-takers did the model correctly classify as such. Specificity refers to classification of true negatives, i.e. how many of the non-excessive risk-takers did the model correctly classify as such. The sensitivity and specificity of a model are trade-offs. If we increase specificity, the sensitivity will go down. Prioritizing the sensitivity will ensure that many of the excessive risk-takers are identified as such, but at the cost of incorrectly identifying non-risk takers as risk-takers (Florkowski, 2008). In the current dataset we measured the outcome variable, DOSPERT scores, as a continuous variable. To show the utility of this type of modeling, here we simulate 4 potential scenarios in which we classify participants as excessive risk takers based on these continuous DOSPERT scores. We divided the DOSPERT total scores at time point 2 into 5 quintiles (Q1-Q5) and then constructed the following scenarios: 1) Q1 non-excessive, Q2-Q5 excessive, 2) Q1-Q2 non-excessive, Q3-Q5 excessive, 3) Q1-Q3 non-excessive, Q4-Q5 excessive and 4) Q1-Q4 non-excessive, Q5 excessive. For each of these 4 alternatives for the dichotomous indicator “risk-taking” at time point 2 we trained a 5-fold cross-validated LASSO model. We used all available predictors as input variables in these models. To evaluate model performance, we plotted a nonparametric ROC curve using the test set and each possible outcome of the diagnostic risk-taking test as a classification cut point. These points are then connected by straight lines, and the area under the resulting ROC curve is computed using the trapezoid. We then compute the corresponding sensitivity and specificity of the model. Model performance for the dichotomous outcome variables was evaluated based on the overall area under the ROC curve, and the specificity and sensitivity plots of the model. Based on the output of the model we can also determine a criterion value. The criterion value is the predicted probability returned by the model at which the researcher or clinician decides at

time t that the individual is at risk for displaying excessive risk taking at $t+2$.

Results showed that AUC-ROC and specificity/sensitivity performance measures are best in the scenario that Q1-Q2 are defined as non-excessive risk takers and Q3-Q5 are defined as excessive risk takers. In this scenario the model performs quite well with a ROC-AUC of .77, see Tables 4 and 5. In this scenario the intersection of the specificity/sensitivity plot is at a predicted probability of excessive risk taking at time point 2 of .59 see Figure 1. This means that if you were to offer a prevention programme to all participants with a predicted probability of excessive risk taking behaviour at the initial measurement point of 59%, the sensitivity and the specificity would both be 74%.

Discussion

In the current study we compared four different estimation models to predict the probability of future risk taking behavior two and four years later. Results show that the LASSO machine-learning algorithm outperforms the more traditional OLS regression approaches out-of-sample two years later, but not four years later. Furthermore, we show that the machine learning results can be used to classify a criterion value of who is at risk for excessive risk taking. Together these results show that machine learning is a promising new direction in prediction of risk taking and this study opens up a new approach to early identification of future risk taking behavior in adolescence.

OLS approaches vs LASSO comparisons

The first question we addressed in this paper is which method is better suitable to predict risk taking behavior out-of-sample. Results show that the LASSO model performs better than the OLS regression approach when predicting the likelihood of risk-taking behavior two years later. The LASSO model was able to predict 20% of the variance of risk taking behavior two years later. However, it is important to keep in mind that the objective of Lasso is to predict the outcome optimally and not to infer the causal relationship between independent and dependent variable(s). This means that the variables identified by the

machine learning model are those that show high predictive power, irrespective of whether this represents a causal relationship. To illustrate this, we can look at the relationship between therapy and symptom severity. In an observational data set, you are likely to observe a positive correlation between the number of therapy sessions and severity of the condition that led to seeking treatment. Yet, at the same time –assuming treatment is effective– the causal effect of the number of therapy sessions spent and symptom severity is expected to be negative instead (i.e more therapy will lead to lower levels of symptoms). Although the model does not test for causal relationships, predictive modeling and can provide new insights into the trajectories of adolescent development on the theoretical level. The model can identify variables that were previously not included in theoretical models. Future research can test the causal relationship of these variables. Furthermore, prediction analyses at the individual level are complementary to explanatory statistical models at the group level.

Using LASSO for identification of a target group for prevention of risk taking behavior

We used LASSO models to classify adolescents as at risk or not at risk for excessive risk taking. We showed that, if the true division of excessive and non-excessive risk takers is indicated by classification of DOSPERT scores in which quintile 1 and 2 are non-excessive risk takers and quintile 3-5 are excessive risk-takers, the model can correctly classify 77% of the individuals who will fall in the category of excessive risk takers two years later. This means that if we measure the variables that are retained in the final model on a new population, this model can be used to target specific individuals for prevention efforts. An example of a prevention effort could be a targeted prevention programme. The model shows that if we would use the criterion value of .59 identified by the model to enroll participants in a prevention programme the sensitivity is 74%. This indicates that 74% of the individuals who will not become excessive risk takers are correctly classified as non-excessive risk takers

and 26% of the excessive risk takers would not be enrolled in the prevention programme.

Limitations and future directions

Before these models can be used in practice, there are several questions that future work should address. Firstly, future work should test the generalizability of the current findings. Specifically, future work should focus on testing whether the currently used machine learning model, i.e. LASSO, outperforms traditional regression techniques in other samples. Secondly, future work should compare different types of machine learning models and test whether LASSO is the best model for out-of-sample prediction. LASSO can be compared with other machine learning models for supervised learning such as random forest models, regression trees, support vector machines, neural nets, matrix factorization (Athey, 2018). Thirdly, the true power of the predictions shown in the current study is that these results give us a handle on targeting prevention efforts to a specific population. Prevention efforts are costly and work best if the correct target group is identified early on. Here we show that machine learning is a useful tool to identify the future target population. However, the current study tested a typically developing sample and did not focus on adolescents at risk for excessive risk taking. For the current models the confidence interval of the AUC is very large for the models with the largest difference between the number of participants in each group, i.e. the models classifying Q1 as non-excessive risk taking and Q2-5 as excessive risk taking and the model in which we classify Q1-4 as non-excessive risk taking and Q5 as excessive risk taking. This shows that to use LASSO as a method to classify adolescents and to use these models for enrolment in prevention programmes, more data is needed to increase prediction accuracy at the end points of the distribution. To generalize the current findings and test whether the same variables are meaningful predictors for future excessive risk taking, future work should focus on an at-risk population. Lastly, the strength of the machine learning approach is that all independent variables can be considered in the prediction model. This implies that for future work it is of crucial importance to ensure that

516 a rich set of independent variables are collected such that the advantage of machine learning
517 models can be fully exploited.

518 **Conclusion**

519 Taken together, the current study shows that machine learning can be used to predict
520 the likelihood of future risk taking behavior. The results of these prediction analyses can be
521 used to identify a target population for (clinical) interventions early on. Here we show that
522 machine learning is a promising new approach for prediction of behavior. Future work
523 should aim to collect a rich set of independent variables to allow for use of machine learning
524 techniques.

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Tables

Table 1

Descriptive statistics of all variables.

	n	Mean/ count	sd	min	max
<i>Background variables</i>					
Age (T)	298	13.96	3.65	8.01	25.95
Age (T+2)	286	15.81	3.54	9.92	26.62
Age (T+4)	274	17.88	3.65	11.94	28.72
Sex (females)	298	146			
<i>Predictor variables</i>					
PDS	236	2.41	0.87	1	4
Testosterone (pmol/ml)	259	109.88	159.52	4	915
Estradiol	276	2.4	1.64	0	13.97
DHEA	275	462.19	734.87	0.72	6541.31
COMT (val/val)	295	62			
COMT (val/met)	295	144			
COMT (met/met)	295	89			
DAT1 (9/9 and 9/10)	262	123			
DAT1 (10/10)	262	139			
IQ	294	109.63	10.42	80	142.5
Verbal IQ	294	112.09	12	75	145
Performal IQ	294	107.18	14.32	65	140
BART total number of explosions	294	10.86	3.81	2	24
BART mean number of successful pumps	261	5.38	2.42	1.17	15.2
Delay discounting indifference points:					
- 2 days	294	8.47	2.27	0	10
- 30 days	294	6.05	3.39	0	10
- 180 days	294	3.95	3.48	0	10
- 365 days	294	3.01	3.28	0	10
Delay discounting AUC	294	0.44	0.3	0	1
Delay discounting mean reaction time (seconds)	294	3.23	1.25	1.43	1.11

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Table 1

Continued.

	n	Mean/ count	sd	min	max
Mental counters accuracy	288	0.81	0.16	0.06	1
Ultimatum game offer	295	4.62	1.16	0	9
Ultimatum game response (reject)	294	224			
Nucleus Accumbens (win>lose)	245	1.91	2.31	-7.79	8.15
Task rating - Win for self	261	8.26	1.9	0	10
Task rating - Lose for self	260	3.12	2.12	0	10
Task rating - Win for friend	293	7.74	1.86	0	10
Task rating - Lose for friend	292	3.51	2.16	0	10
Task rating - Friend deserves (believe)	291	8.12	1.81	0	10
Task rating - Friend deserves (think)	292	8.34	1.64	1	10
BISBAS BIS	277	19.52	3.81	9	28
BISBAS Drive	277	10.74	2.22	6	16
BISBAS Fun Seeking	277	11.6	1.9	7	16
BISBAS Reward Sensitivity	277	17.22	1.85	10	20
BIS-11	269	61.26	8.99	36	88
BPAQ Physical aggression	277	26.81	6.12	15	44
BPAQ Verbal aggression	277	20.16	3.67	6	31
BPAQ Anger	277	21.23	4.57	10	37
BPAQ Hostility	277	22.16	8.07	8	45
EAQ Differentiating emotions	190	17.94	2.92	8	21
EAQ Verbal sharing of emotions	190	6.77	1.86	3	9
EAQ Not hiding emotions	190	10.03	2.42	5	15
EAQ Bodily awareness of emotions	190	9.13	2.69	5	15
EAQ Attending to others' emotions	190	13.25	1.93	7	15
EAQ Analyses of (own) emotions	190	11.08	2.41	5	15
FQS positive	277	4.27	0.49	2.85	5
FQS negative	277	1.63	0.55	1	3.71
NEO PI Anxiety	190	23.03	7.67	8	47

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Table 1

Continued.

	n	Mean/ count	sd	min	max
NEO PI Depression	190	21.82	11.62	8	55
NEO PI Impulsiveness	190	24.65	8.13	8	46
Age first sip alcohol	117	14.18	1.95	6	19
Age first time drunk	77	15.68	1.82	12	22
Alcohol use last week	189	6.69	15.21	0	90
Alcohol use last month (glasses)	136	7.45	13.58	0	50
Alcohol use lifetime (glasses)	136	30.18	38.38	0	91
Age first cigarette	71	14.92	2.46	10	28
Cigarette use last week	190	0.99	3.64	0	20
Age first marijuana	55	16.15	2.56	11	24
Marijuana use (lifetime)	190	1.4	4.2	0	20
Age first harddrugs	11	18.82	2.55	16	23
<i>Outcome variable</i>					
DOSPERT total score (T+2)	211	126.62	29.82	43	204
DOSPERT total score (T+4)	238	117.9	28.5	46	201

Table 2

In and out-of-sample model performance for all models with likelihood of risk taking two years ($t+2$) and four years ($t+4$) after the initial measurement as dependent variable. Preferred models are indicated in bold.

		OLS				LASSO			
		theory-driven		stepwise backwards		kitchen sink		λ -opt = 10.45	
		t+2	t+4	t+2	t+4	t+2	t+4	t+2	t+4
	# predictors	8	8	10	8	79	79	19	20
in-sample	R-squared	0.26	0.16	0.47	0.36	0.73	0.61	0.51	0.36
	RMSE	25.5	26.5	21.7	24.0	15.3	18.0	21.6	23.9
df-adjusted in-sample	R-squared	0.22	0.11	0.42	0.27	0.41	0.25	0.44	0.27
	RMSE	26.3	27.2	22.6	24.7	22.8	25.0	23.3	25.6
out-of-sample	R-squared	0.16	0.13	0.07	0.09	0.04	0.09	0.20	0.09
	RMSE	27.6	25.8	31.2	28.5	40.4	42.7	26.8	26.7

Table 3

Retained variables in LASSO model for the prediction of likelihood of risk taking at time point 2 (t+2 years).

	Variable	LASSO coefficient
Measured	PDS	2.44
	Testosterone	.026
	Estradiol	.623
	Delay discounting mean reaction time	-.003
	BISBAS BIS	-.914
	BISBAS Drive	1.22
	BIS-11	.395
	BPAQ Physical aggression	.571
	BPAQ Verbal aggression	.337
	EAQ Not hiding emotions	.442
	EAQ Analyses of (own) emotions	-.133
	Marijuana lifetime use	.277
Missing	PDS	-1.22
	DHEA	6.78
	EAQ Differentiating emotions	-2.39
	Age first sip of alcohol	-1.86
	Alcohol use last week	-2.39
	Cigarettes use last week	-2.39
	Marijuana lifetime use	-8.30

Table 4

Out-of-sample Area Under the ROC Curve (AUC) and the 95% confidence interval (CI) of the AUC for each of the four classification scenarios. Q refers quintile, used to construct potential scenarios of classification into excessive and non-excessive risk taking.

Scenario	Q1 Q2-Q5	Q1-Q2 Q3-Q5	Q1-Q3 Q4-Q5	Q1-Q4 Q5
Out-of-sample AUC	.68	.77	.70	.64
95% CI	.52-.84	.66-.89	.57-.83	.45-.83

Table 5

Retained variables and estimates for each of the four potential scenarios for the classification of excessive risk takers at time point 2 ($t+2$ years).

	Scenario			
	Q1 Q2-Q5	Q1-Q2 Q3-Q5	Q1-Q3 Q4-Q5	Q1-Q4 Q5
Number of predictor variables	24	13	18	14
Variables				
Measured				
PDS	.0394	.0332		.0467
Testosterone		.0004	.0002	.0001
Estradiol	.0218	.0228		
BART total number of explosions	.0007	.0043		
Delay discounting indifference point 2 days		.0014		
Delay discounting indifference point 30 days			.0065	
BISBAS BIS	-.0107	-.0094	-.0146	-.0009
BISBAS Drive			.0066	.0121
BISBAS Fun Seeking	.0190			
BISBAS Reward Responsiveness	-.0009			
BIS-11	.0010		.0059	.0027
BPAQ Physical aggression	.0014	.0113	.0156	.0081
BPAQ Verbal aggression		.0118	.0109	
BPAQ Hostility	.0051			
EAQ Attending to others' emotions	-.0095			
EAQ Not hiding emotions			.0111	
EAQ Analyses of (own) emotions				-.0004
NEO PI Anxiety				-.0019
NEO PI Depression			-.0031	
Task rating - Win for self	.0304			
Task rating - Win for friend			-.0061	-.0067

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Table 5

Continued.

	Scenario			
	Q1 Q2-Q5	Q1-Q2 Q3-Q5	Q1-Q3 Q4-Q5	Q1-Q4 Q5
Task rating - Friend deserves (think)	.0092			
Alcohol last month	.0016			
Age first time drunk			.0026	
Age first cigarette	-.0047	-.0282		
Marijuana lifetime use			.0055	.0036
Age first marijuana				-.0003
Age first harddrugs			.0318	
Missing				
PDS	-.0533		-.0251	
Testosterone	-.0340			
Estradiol		.0433		
DHEA	.1399		.1349	
EAQ Differentiating emotions	-.0258	-.0592	-.1159	-.0120
Mental Counters Accuracy	.1024		-.0949	
Nucleus Accumbens win>lose	-.0850			
Age first sip of alcohol	-.0790			-.0007
Alcohol use last week in glasses	-.0258	-.0592	-.0786	
Cigarettes last week	-.0205	-.0303		
Weed lifetime use	-.1251			-.0006

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Figures

Figure 1. Sensitivity/specificity plots for each of the four potential scenarios in which participants were classified as excessive risk takers or non-excessive risk takers based on their DOSPERT scores at time point 2. Plots show the sensitivity curve and specificity curve for each of the four scenarios. Q refers to quintile of DOSPERT scores, based on which participants were classified as non-excessive or excessive risk taker. Specificity/sensitivity trade-off was optimal for the scenario in which participants with DOSPERT scores in Q1-2 were classified as non-excessive risk takers and Q3-5 as excessive risk takers.