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Predicting suicidal ideation in primary care: An approach to identify easily assessable key variables

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ABSTRACT

Objective: To obtain predictors of suicidal ideation, which can also be used for an indirect assessment of suicidal ideation (SI). To create a classifier for SI based on variables of the Patient Health Questionnaire (PHQ) and sociodemographic variables, and to obtain an upper bound on the best possible performance of a predictor based on those variables.

Methods: From a consecutive sample of 9025 primary care patients, 6805 eligible patients (60% female; mean age = 51.5 years) participated. Advanced methods of machine learning were used to derive the prediction equation. Various classifiers were applied and the area under the curve (AUC) was computed as a performance measure.

Results: Classifiers based on methods of machine learning outperformed ordinary regression methods and achieved AUCs around 0.87. The key variables in the prediction equation comprised four items - namely feelings of depression/hopelessness, low self-esteem, worrying, and severe sleep disturbances. The generalized anxiety disorder scale (GAD-7) and the somatic symptom subscale (PHQ-15) did not enhance prediction substantially.

Conclusions: In predicting suicidal ideation researchers should refrain from using ordinary regression tools. The relevant information is primarily captured by the depression subscale and should be incorporated in a nonlinear model. For clinical practice, a classification tree using only four items of the whole PHQ may be advocated.

1. Introduction

According to a review [1] including 40 studies, 45% of individuals who died by suicide had contact with primary care providers within 1 month prior to suicide and 75% of the individuals who died by suicide had contact within the year of suicide. Given that the majority of the individuals who commit suicide make contact to primary care providers in previous months, an appropriate screening of individuals at the level of the primary care setting might help to initiate proper interventions in order to prevent suicide.

Primary care physicians have to be aware of the prevalence (the figures vary between 1 and 10% [2]) of patients who experience suicidal thoughts [3]. Moreover, adequate assessment tools have to be known and available. However, the prediction of suicidal ideation (SI) at this level can be a challenging issue, as the underlying population is not a high-risk population which in turn implies relatively low base rates. Nevertheless, results from studies examining 1) SI within patients with anxiety disorders [4], 2) SI within somatoform disorders [5] and 3) SI within patients diagnosed with depression [6] suggest that the usage of item batteries which reflect these constructs (accompanied with known predictors on the sociodemographic level such as age) could also be used within a non-preselected sample in order to screen for SI.

In particular, the 9th item of the Patient Health Questionnaire depression scale (PHQ-9) [7] - a scale which is routinely used in the clinical context - has been widely used to assess suicidal ideation. Endorsement to the item has been identified as a consistent predictor of suicide attempts and suicide deaths in large primary care and population-based analyses [8,9,11]. Of those patients reporting SI, around 32% will make a suicide attempt at some point in their life [12]. Besides directly asking for suicidal thoughts and ideations, taking into account additional relevant variables, especially depressive symptoms and known risk factors such as gender or age, can improve the detection of suicide risk [8,9]. In psychiatric epidemiology or in general population studies, for reasons of liability, the 9th item of the PHQ-9 is frequently not included, and instead of the PHQ-9, the 8-item version of the Patient Health Questionnaire (PHQ-8) [14] that omits the suicidal ideation item, is used. In these studies, the results of our study might

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provide a valuable method for imputing the ninth item and for assessing suicide risk in the investigated population.

The aim of this study – among assessing the base rate of SI in primary care - was to confirm and identify relevant risk factors for suicidal ideation and to determine their relative importance in predicting SI, whereby SI is operationalized via the response on the 9th PHQ item. We aimed to create a prediction equation based on the PHQ on item level and sociodemographic variables using advanced methods of machine learning. By using methods of machine learning rather than ordinary regression models the resulting predictions can in general reflect much more complicated relationships between the variables and the outcome (suicidal ideation). Knowledge of these predictors can aid the primary care physician in detecting patients with SI and can also serve as a tool for a brief, initial assessment which can then, dependent on the outcome, be followed by a more precise and prolonged method of assessment, like e.g. the Columbia-suicide severity rating scale (C-SSRS) [15]. Moreover, in practical cases, wherein directly asking a patient about the topic of suicidal ideation is not endorsed or in cases wherein the response on the 9th item is missing, the results of accurate classifiers can serve as a valuable proxy for the unknown response.

2. Methods

2.1. Design and sample

For this study, we used cross-sectional data from a broad screening assessment performed in 33 primary care practices located in the metropolitan area of Hamburg, Germany, from 2011 [16] to 2014. Data collection was part of a study evaluating the Network for Somatoform and Functional Disorders (*Sofu-Net*) [16,17]. Patients were asked to complete a screening questionnaire after providing oral informed consent while waiting for the consultation (no reimbursement was given). Having severe somatic or psychiatric disease, severe cognitive disabilities, being younger than 18 years old, having impaired vision, and insufficient German language skills defined exclusion criteria.

The practices were approached on two to four consecutive days and each patient who gave consent provided sociodemographic data and was assessed via the Patient Health Questionnaire (PHQ). Ethics approval was obtained from the Medical Chamber Hamburg, Germany.

2.2. Instruments

The three subscales GAD-7, PHQ-9 and PHQ-15 of the Patient Health Questionnaire – which are routinely applied in clinical settings - were used to measure generalized anxiety, depression and somatic symptoms. Each of the seven GAD-7 items has a score range from 0 to 3 (the same holds for each one of the PHQ-9 items), while the items of the PHQ-15 are scored from 0 to 2. Whenever we refer to an item of these scales, we use the score on this item in the statistical analysis. The PHQ-8 – i.e. the PHQ-9 without the 9th item assessing suicidal ideation – is used in the analysis as a predictor instead of the PHQ-9 to avoid circularity. The PHQ scales have good psychometric properties which are summarized in Kroenke et al. [7].

The 9th PHQ-9 item concerning suicidal ideation serves as the dependent variable in this study. Participants are asked to indicate on an ordinal measurement scale how often they experienced suicidal thoughts ("thoughts that you would be better off dead or of hurting yourself in some way") within the last two weeks. Although there are four possible values (0 = not at all; 1 = several days, 2 = more than half the days, 3 = nearly every day), we decided to dichotomize the item for primarily reasons of statistical precision (and for ease of interpretation). That is, categories 2 vs. 3 might for example be very difficult to distinguish properly, whereas the comparison of 0 vs other categories enables more sharp distinctions. Moreover, as shown in the Results section, some categories are rather sparsely chosen which limits the power of any method to detect the corresponding class membership. Hence, the item was dichotomized with 0 referring to no suicidal thoughts, whereas responding in any of the three remaining categories was coded with 1. This cut-off was chosen to provide a rather sensitive definition of SI.

2.3. Statistical analysis

We used methods of pattern recognition in order to discern patients with no SI from patients with SI.

Our aim was twofold: By reporting results of models of pattern recognition (see below), we sought to provide an estimate for the best possible prediction of SI one can achieve using the variables at hand. However, due to practical necessities (i.e. a classifier has to be easily applicable in order to be adapted in practice) we also incorporated results of classifiers which are more restrictive. Where by the term "classifier", we mean a function which takes as input the measurements of a patient on several variables (e.g. PHQ-9 items) and outputs a probability that this patient belongs to the group of patients with suicidal thoughts.

Secondly, we distinguished between three blocks of predictor variables which serve as input for the various classification methods:

1) Demographic variables (age, gender, education and marital status) 2) Variables of the Patient Health Questionnaire on the item level (all items of the PHQ-15, PHQ-8 and GAD-7 items) 3) Composite scores derived from the PHQ (PHQ-8 score; GAD-7 score and PHQ-15 score).

Each classification method was applied to each block in order to gain insight into the predictive power at the demographic, the item and the scale score level. In a final analysis each classifier was also applied for the whole set of variables. The derivation and evaluation of each prediction equation was done in two steps: Firstly, a training sample (randomly chosen half of the data set) was used to learn the classifier. In a second step, the model derived in the first step was used to predict class membership probability for each entry of the test sample (the remaining half of the data set). The predicted probabilities were dichotomized for a continuum of cut-off scores and an approximate measure of the area under the resulting ROC-curve was computed for the performance of the classifier (see also Section 3 and the corresponding footnote).

We distinguish the following methods:

Method 1: classification trees

For each variable, and each potential cut-off value for this variable, a split according to the cut-off is applied and the conditional class probabilities for SI of the resulting split categories are examined. The variable and the cut-off for which splitting results in partitions with strong informative conditional class probabilities is chosen first and splitting continues within the partitioned data set provided by the first split (we used the process implemented in the R function "tree" with default settings). For full description see [18].

Method 2: the Support Vector Machine (SVM)

This method [19] provides highly flexible classifiers by seeking to separate classes in a transformed feature space via methods of convex analysis. The method incorporates two tuning parameters (we optimized the classifier over a grid specified by the "gamma"-vector (0.1, 0.2, …, 0.9, 1, 2, …,10) and the "cost"-vector (1, 2, …, 10, 100, 1000)) representing attributes of an underlying radial kernel function and penalties for non-perfect separation which regulate the generalization error.

Basically, each group – those with and those without SI – can be depicted in a multidimensional space, wherein the coordinates are given by the values of the predictor variables (or by properly transformed values thereof). If the corresponding "clouds" of SI vs. non-SI patients can be separated by some line, then a SVM classifier will be able to find this separation. In general, with SVMs it becomes possible to capture much more complex relationships than with ordinary logistic regression models.