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CLINICAL RESEARCH ARTICLE

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Should I stay or must I go? Predictors of dropout in an internet-based psychotherapy programme for posttraumatic stress disorder in Arabic

Max Vöhringer[a,b], Christine Knaevelsrud [b], Birgit Wagner[c], Martin Slotta[b], Anne Schmidt[a], Nadine Stammel[a,b] and Maria Böttche[a,b]

[a]Center Überleben gGmbH, Berlin, Germany; [b]Department for Clinical-Psychological Intervention, Freie Universität Berlin, Berlin, Germany; [c]Medical School Berlin, Berlin, Germany

ABSTRACT

Background: Dropout from psychotherapy has negative impacts on clients, therapists, and health-care agencies. Research has identified a variety of variables as predictors of dropout, which can be grouped in three domains: socio-demographic, psychological, and treatment-related variables.
Objective: In order to further clarify the question of predictors of dropout, an exploratory research design was applied to a large sample, testing 25 different variables from the three domains as possible predictors.
Method: The sample included 386 adults who started an internet-based cognitive-behavioural treatment approach for posttraumatic stress disorder (PTSD) in Arabic. As the participants had different countries of origin and of current residence, multilevel analyses were performed. For the selection of predictor variables, the Least Absolute Shrinkage and Selection Operator was used.
Results: Dropout rates did not vary significantly between participants from different countries of origin or from different countries of residence. Likewise, dropout did not vary significantly between clusters of individuals with the same country of origin and the same country of residence, i.e. the same migration path. Three of the 25 variables were identified as significant predictors for dropout: marital status (divorced participants' probability to drop out was higher compared to non-divorced, i.e. single, married, or widowed, clients), treatment credibility scores (higher dropout probability of participants with lower treatment credibility), and the participants' year of registration for the treatment (earlier years of registration predicted lower dropout probability). The overall ability of the three-factor-model to discriminate between dropout and completion was poor (AUC = 0.652, with low sensitivity and acceptable specificity).
Conclusions: The predictors belong to the treatment-related domain (credibility, year of registration) or are specific to the target group (marital status). However, the results show that predicting treatment dropout continues to be a very challenging endeavour and indicate that it is important to look at each intervention individually.

¿Debería quedarme o debo irme? Predictores de abandono en un programa de psicoterapia basado en internet para trastorno de estrés postraumático en árabe

Antecedentes: El abandono de la psicoterapia impacta negativamente en los clientes, terapeutas y agencias de cuidado de la salud. Los estudios han identificado una diversidad de variables como predictores de abandono, las cuales pueden ser agrupadas en tres dominios: socio-demográficas, psicológicas y relativas al tratamiento.
Objetivo: Para aclarar más la pregunta sobre los predictores de abandono de la psicoterapia, se aplicó un diseño de estudio exploratorio a una muestra grande, evaluando 25 diferentes variables de los tres dominios, como posibles predictores.
Método: La muestra incluyó 386 adultos que iniciaron un enfoque de tratamiento cognitivo-conductual basado en internet para el trastorno de estrés postraumático, en árabe. En la medida que los participantes tenían diferentes países de origen y de residencia actual, se realizaron análisis multinivel. Para la selección de las variables predictoras se utilizó el método LASSO (Least Absolute Shrinkage and Selection Operator, por su sigla en inglés).
Resultados: Las tasas de abandono no variaron significativamente entre los participantes de diferentes países de origen o de diferentes países de residencia. Igualmente, el abandono no varió significativamente entre grupos de individuos con el mismo país de origen y el mismo país de residencia, es decir, con la misma vía de migración. Tres de las 25 variables fueron identificadas como predictores significativos de abandono: estado civil (la probabilidad de abandono de los participantes divorciados fue mayor comparado a los no divorciados, es decir clientes solteros, casados o viudos), puntajes de credibilidad del tratamiento (mayor probabilidad de abandono de participantes con menor credibilidad del tratamiento), y el

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关键字
辍学; 损耗; 预测因子; 创伤; 创伤后应激障碍; 心理治疗; CBT; 基于互联网的干预; 阿拉伯

HIGHLIGHTS
- Predictors of psychotherapy dropout were investigated in an internet-based psychotherapy programme for posttraumatic stress disorder in Arabic.
- Of the 25 variables that were tested as predictors, three proved to be significant: the marital status (higher dropout for divorced participants), the treatment credibility scores (higher dropout with lower credibility), and the year of registration (lower dropout in earlier years).
- The ability of this three-factor model to discriminate between dropout and completion was limited.

CONTACT Maria Böttche maria.boettche@fu-berlin.de Freie Universität Berlin, Habelschwerdter Allee 45, 14195 Berlin, Germany
Supplemental data for this article can be accessed here.

año de registro en el tratamiento de los participantes (año de registro más antiguo predijo menor probabilidad de abandono). La capacidad global del modelo de tres factores para discriminar entre abandono y término fue pobre (AUC=0.652, con baja sensibilidad y especificidad aceptable).
Conclusiones: Los predictores pertenecen al dominio relativo al tratamiento (credibilidad, año de registro) o son específicos al grupo objetivo (estado civil). Sin embargo, los resultados muestran que la predicción del abandono de tratamiento en psicoterapia continúa siendo una tarea muy desafiante e indican que es muy importante mirar cada intervención de forma individual.

我应该坚持还是放弃？基于互联网的创伤后应激障碍治疗计划在阿拉伯的脱落预测

背景: 心理治疗的脱落会对来访者，治疗师和医疗保健机构产生负面影响。研究已经识别各种脱落预测因素, 可分为三个方面:社会人口统计学, 心理和治疗相关的变量。
目的: 为了进一步阐明心理治疗脱落的预测因素, 将探索性研究设计应用于一个大样本, 测试了三个方面的25个不同变量的可能预测性。
方法: 该样本包括386位成年人, 用阿拉伯语参加了一项基于网络的认知行为疗法来治疗创伤后应激障碍 (PTSD) 。针对参与者的原籍国和居住国不同, 对数据进行了多层分析。为了挑选预测变量, 使用了LASSO (Least Absolute Shrinkage and Selection Operator) 算法。
结果: 来自不同原籍国或居住国的参与者之间的脱落率差异不显著。同样，在原籍国和居住国相同（即移民路径相同）的人群中，脱落率也没有显著差异。 25个变量中的三个被确定为脱落的重要预测指标:婚姻状况（离婚者的脱落概率要高于未离婚者（即单身，已婚或丧偶)), 治疗信心（较低治疗信心的参与者有较高的脱落概率）以及参与者进行治疗的注册年份（注册的年份较早预测较低脱落概率）。三因素模型区分脱落和完成的能力很差 (AUC = 0.652, 灵敏度较低, 特异性可接受) 。
结论: 预测变量属于治疗相关领域 (信心, 注册年份) 或特定目标人群 (婚姻状况) 。但是, 结果表明，预测心理治疗中的脱落仍然是一项具有挑战性的工作，并且单独分析每种治疗方法非常重要。

1. Introduction

In general, clients of psychotherapy who discontinue treatment prematurely are referred to as dropouts, in contrast to completers of therapy (Fernandez, Salem, Swift, & Ramtahal, 2015). In addition, participants are also referred to as dropouts if they have not achieved a certain number of therapy sessions according to the treatment protocol or after the first session (Gutner, Gallagher, Baker, Sloan, & Resick, 2016). The lack of a standardized operational definition of dropout is a major methodological challenge for the aggregation of findings of dropout research (Fernandez et al., 2015; Melville, Casey, & Kavanagh, 2010). However, most commonly dropout is defined as 'termination at any point between registering for treatment and completing post-treatment questionnaires' (Melville et al., 2010, p. 457). Furthermore, it is then differentiated between pre-treatment dropout (prior to the first session), treatment dropout (failure to complete the therapy), and follow-up dropout (prior to completing follow-up assessments; Melville et al., 2010).

Dropout has been shown to have negative impacts on clients, therapists, and health-care agencies (Barrett, Chua, Crits-Christoph, Gibbons, & Thompson, 2008; Swift & Greenberg, 2012). Even though it should be mentioned that there may also be positive causes for dropout such as an early improvement and a decreasing need for psychotherapy (e.g. Lester, Artz, Resick, & Young-Xu, 2010), treatment outcomes of clients who dropped out are most often poorer than those of completers (Donkin et al., 2011; Lampropoulos, 2010; Lutz et al., 2014). The analysis of underlying causes of dropout is important in order to develop strategies to address the problem. Research is being undertaken in this field in order to determine its magnitude (i.e. how much dropout occurs) and timing (i.e. at which point treatment processes are terminated; e.g. Swift, Greenberg, Tompkins, & Parkin, 2017; van Ballegooijen et al., 2014). Furthermore, the question of predictor variables of dropout has gained importance (Fernandez et al., 2015). One of the few theoretical models to explore psychotherapy dropout is the cognitive model by Liese and Beck (1997). It describes how various aspects put clients at risk for dropping out by activating negative beliefs about the success of the treatment. These aspects are grouped into socio-demographic, psychological, and treatment-related predictor variables.

Meta-analyses and reviews on the topic of psychotherapy dropout have been carried out with various specific focuses in recent years (Fernandez et al., 2015; Imel, Laska, Jakupcak, & Simpson, 2013; Kayrouz et al., 2018; Kuester, Niemeyer, & Knaevelsrud, 2016; Melville et al., 2010; Swift & Greenberg, 2012; Swift et al., 2017; van Ballegooijen et al., 2014). Summarizing those that analyse PTSD-specific treatments together with interventions for other disorders, they have shown the substantial magnitude of treatment dropout, with mean dropout rates ranging between 19.7% (Swift & Greenberg, 2012) and 34.9% (van Ballegooijen et al., 2014). Internet-based therapies typically have higher rates than face-to-face interventions (mean dropout rates of 34.2% vs. 25.1%; Fernandez et al., 2015). The findings about predictors of dropout are, however, mostly inconsistent: Depressive disorders, for example, are associated with the lowest (17.4%, Swift & Greenberg, 2012) or with the highest (36.4%, Fernandez et al., 2015) dropout rates. While Swift and Greenberg (2012) assessed an existing relationship as a protective factor against dropout, relationship has also been associated with a higher dropout probability (Melville et al., 2010). In addition, a number of moderating factors have been identified in some meta-analyses but could not be verified in others, e.g. education (Melville et al., 2010; Swift & Greenberg, 2012) or number of sessions offered (Fernandez et al., 2015; Swift & Greenberg, 2012). The only predictors for which evidence from more than one meta-analysis or review was found are age (less dropout with increasing age; Melville et al., 2010; Swift & Greenberg, 2012), and gender (more dropout associated with male gender; Melville et al., 2010; Swift & Greenberg, 2012).

The meta-analyses by Imel et al. (2013) and Kuester et al. (2016) analysed dropout in specific treatments for PTSD, the latter focussing exclusively on internet-based interventions. They verified the finding of higher dropout rates for internet-based therapies: Kuester et al. (2016) found an average dropout rate of 23.2%, while Imel et al. (2013), who analysed internet-based-interventions together with face-to-face-interventions, found a rate of 18%. Their findings about predictors of dropout are, however, inconsistent, too: Imel et al. (2013) identified group modality and a greater number of sessions (but not differences in trauma focus, as hypothesized) as dropout predictors. Kuester et al. (2016), on the contrary, found a significant effect of baseline PTSD symptoms with lower symptoms of dropouts than of completers. Interestingly, Kuester et al. (2016) did not verify the age and gender effects identified in non-PTSD-specific analyses (these effects were not analysed by Imel et al., 2013).

It must be concluded that the question of predictors of psychotherapy dropout has still not been clarified sufficiently. It is the aim of the present study to address this gap by applying an exploratory research design to a large sample (N = 386) and by including a large number of predictor variables by means of an innovative statistical methodology. The object of analysis is an internet-based psychotherapy programme for PTSD, which is offered in Arabic language. Thus, in addition to general findings about psychotherapy dropout, insights are generated specifically for internet-based interventions and for Arab populations, the latter being strongly underrepresented in psychological research (Abudabbeh & Hays, 2006; Kayrouz et al., 2018).

The ambivalence of existing findings of psychotherapy dropout research does not presuppose distinct and directed hypotheses for this study. Thus, it is analysed exploratorily which of a variety of socio-demographic, psychological, and treatment-related factors are most predictive for treatment dropout. To elaborate, these factors are gender, age, marital status, number of children, education, country of origin, country of residence, and migration status of participants in the socio-demographic domain, posttraumatic symptom severity, type of trauma, depression, anxiety, and quality of life in the psychological domain, and treatment credibility and year of registration in the treatment-related domain. In addition, non-linear, i.e. quadratic, relationships between interval-scaled predictors and dropout probability are included in the analysis to further broaden the scope of possible findings.

2. Method

2.1. Participants

The study is part of a programme which exists since 2008 and offers internet-based treatment for PTSD and depression to Arabic-speaking individuals who are living in the MENA region (Middle East & North Africa). The present study is an open-label dissemination study of the PTSD treatment (i.e. only one treatment offered); therefore, the study included 386 Arabic-speaking adults (268 female, 69.4%) from the MENA region who took part in the internet-based treatment for PTSD between May 2013 and January 2018. The programme is offered by a psychosocial centre which also treats victims of torture and war and is based in Germany.

Advertisements on the internet and through print media, radio, and television were used to recruit participants. The programme website provided general information about PTSD, depression, the treatment programme and alternatives, and the study. Participants were informed that their data would be protected by rigorous security measures.

To be included in the study, participants had to suffer from a PTSD according to the Diagnostic and Statistical Manual of Mental Disorders (the diagnosis was based on the criteria defined by DSM-IV until February 2017, from then on based on those defined by DSM-5; American Psychiatric Association, 1994; 2013, respectively). Further eligibility requirements were knowledge of Arabic language, a minimum age of 18 years, and access to the internet.

Exclusion criteria were high risk of suicide, psychotic symptoms, substance abuse or dependence, current receipt of psychotherapeutic treatment elsewhere, recent changes in psychotropic medications, current pregnancy, and very high depressive pathology. The depressive symptoms were assessed with the online-administered Beck Depression Inventory II (BDI-II; Beck, Steer, & Brown, 1996) with the cutoff score at BDI-II > 45. All other exclusion criteria as well as the diagnostic criteria of PTSD were assessed with a phone or web-administered clinical interview, i.e. the Composite International Diagnostic Interview (CIDI; Kessler et al., 2004) for DSM-IV and the Structured Clinical Interview (SCID-5; First, Williams, Karg, & Spitzer, 2016) for DSM-5 criteria.

Sociodemographic and psychopathological characteristics of the sample are given in Table 1. Participants from 21 different countries of origin were registered, the five most represented were Egypt (25.4%), Saudi Arabia (12.2%), Syria (11.4%), Algeria (9.1%), and Morocco (8.0%). Regarding the country of current residence, 116 of the participants had migrated from their country of origin so that, in total, 33 different countries of residence were reported (see supplemental material for a total list of countries).

2.2. Treatment

The treatment programme applied was described and analysed in detail by Knaevelsrud, Brand, Lange, Ruwaard, and Wagner (2015). It is based on the Dutch internet-based cognitive-behavioural therapy manual *Interapy* (Lange et al., 2003), which was translated into Arabic and culturally adapted. All therapists were Arabic-speaking mental health professionals (e.g. psychological counsellors, psychologists) living in Egypt or Germany which were continuously trained for internet-based PTSD treatment and attended monthly supervision. Participants were assigned a total of six writing sessions which were structured in two phases: in sensu exposure to the traumatic event and social sharing. The interaction between participants and therapists was asynchronous, i.e. the exchange of written assignments in a secured webportal was not simultaneously. Patients were asked to spend 45 minutes for each assignment and to write a text on the secured webportal during this time. Therapists provided individual feedback and further writing instructions within 48 hours after patients completed each writing assignment. Thus, patients regularly received individual feedback on their written assignments from their personal therapist. If a participant did not complete an essay within one week, the therapists sent him or her a reminder in order to promote adherence. When the deadline expired after one week without a participant's reply, his or her treatment ended. Participants who completed at least four of the six writing assignments were declared *completers*, otherwise they were considered *dropouts*. The efficacy of the programme was assessed in a randomized controlled trial and showed an effect size of d= 0.92 of reduction of posttraumatic stress symptoms in the treatment group relative to a control group (Knaevelsrud et al., 2015).

Table 1. Sociodemographic and psychopathological variables of participants.

Variable	%, *M*	*SD*	Range
Participants according to year of registration (%)			
2013 [a]	7.5	-	-
2014	11.7	-	-
2015	14.8	-	-
2016	24.1	-	-
2017	41.2	-	-
2018 [a]	0.8	-	-
Female gender (%)	69.4	-	-
Age (*M*)	26.00	6.02	18 – 49
Marital status (%)			
Single	72.8	-	-
Married	21.5	-	-
Divorced	5.2	-	-
Widowed	0.5	-	-
Number of children (*M*)	1.48	1.80	0 – 10
Education (%)			
University degree	46.6	-	-
University student	31.1	-	-
High school student or degree	19.4	-	-
Elementary or intermediate school degree	2.8	-	-
Migrated (%)	29.8	-	-
Posttraumatic symptom severity (PDS; *M*)	30.63	10.80	0 – 51
Depression (HSCL-25; *M*)	1.98	0.53	0.00–2.93
Anxiety (HSCL-25; *M*)	1.73	0.66	0.10–3.00
Quality of life (EUROHIS-QOL-8; *M*)	1.33	0.67	0 – 4
Treatment credibility (CEQ; *M*)	19.25	4.38	3 – 27
Type of trauma[b] (%)			
Man-made only	17.6	-	-
Accidental only	9.8	-	-
Man-made and accidental	72.5	-	-

N = 386. *M* = mean, *SD* = standard deviation. PDS = Posttraumatic Stress Diagnostic Scale; HSCL-25 = Hopkins Symptom Checklist-25; EUROHIS-QOL-8 = European Health Interview Survey 8-Item Index; CEQ = credibility/expectancy questionnaire. [a]Participants were recruited from May 2013 to January 2018. [b]See supplemental material for a detailed list of trauma types.

2.3. Measures

The online screening questionnaires inquired sociodemographic data, i.e. gender, age, marital status, number of children, education, country of origin, and country of residence. The migration status was generated from the information given about the country of origin versus the country of residence. In addition, different psychometric questionnaires were applied (for the current study and its hypotheses, four questionnaires were relevant and are described).

Posttraumatic symptom severity was assessed with the Posttraumatic Stress Diagnostic Scale (PDS; Foa, 1995). In the current study, part I of the PDS asking for the types of traumas experienced and part III of the PDS assessing posttraumatic stress symptom severity were examined. Symptom severity is calculated as the sum score of 17 items according to DSM-IV PTSD (intrusions, avoidance, and hyperarousal). Answers to these items are given on a 4-point Likert scale from 0 (not at all or only one time) to 3 (five or more times a week/almost always). The PDS has demonstrated good test–retest reliability (Foa, Cash, Jaycox, & Perry, 1997, Arabic version: Norris &

Aroian, 2008). The internal consistency of the PDS in this sample was α = .86.

Types of trauma experienced were assessed with a list of 24 items (part I PDS and additional traumatic events) with a binomial answer format (yes/no).

Depression and anxiety was measured with the Hopkins Symptom Checklist-25 (HSCL-25; Derogatis, Lipman, Rickels, Uhlenhuth, & Covi, 1974). It consists of 25 items, of which 15 items correspond to depression and 10 items to anxiety symptoms. Answers to each item are given on a 4-point Likert scale ranging from 1 (not at all) to 4 (extremely). For each subscale, average scores are calculated whereas subscale scores >1.75 indicate caseness. The HSCL-25 has been frequently used in different cultural backgrounds and has proved reliable and valid (Al-Turkait, Ohaeri, El-Abbasi, & Naguy, 2011; Ashaba et al., 2018). The internal consistency of the anxiety and depression subscales in this sample were α = .84 and .81, respectively.

Quality of life was measured with the European Health Interview Survey 8-Item Index (EUROHIS-QOL-8; Schmidt, Mühlan, & Power, 2006). Eight items assess the psychological, physiological, social, and environmental dimensions of the construct. Answers are given on 5-point Likert scales (different answering formats) and higher scores indicate a better quality of life. International studies about the psychometric properties of the EUROHIS-QOL -8 found acceptable to good cross-cultural performance and a satisfactory discriminant validity (Rocha, Da, Power, Bushnell, & Fleck, 2012; Schmidt et al., 2006). The internal consistency of the EUROHIS-QOL-8 score in this sample was α = .75.

Treatment credibility was assessed with the credibility/expectancy questionnaire (CEQ; Devilly & Borkovec, 2000) assessing participants' treatment expectancy and credibility before starting the therapy. The CEQ comprises six items that are either rated on a 9-point Likert scale or on a percentage scale ranging from 0% to 100%. Higher values indicate higher treatment expectancy and credibility, each assessed with three items. The subscales have been shown to be stable across different populations and have demonstrated good to excellent reliability (Devilly & Borkovec, 2000). Due to technical problems, only the items 1 to 3 of the treatment credibility scale could be included in the analysis. The internal consistency of this subscale in the sample was α = .74.

2.4. Statistical analysis

All statistical analyses were conducted using R-Studio (Version 1.1.383, 2017). For this study, only complete measures assessed prior to the treatment start were included since variables predictive for dropout are analysed, so that no missing data had to be excluded nor imputed.

As the participants of the study have different countries of origin as well as various countries of current residence, the first step of the statistical analyses was to determine whether a multilevel model was indicated. Thus, two random-intercept models with the clustering of the participants in countries of origin and countries of residence were calculated, respectively. Furthermore, a cross-classified model was computed, which incorporated the clustering of participants in countries of origin *and* countries of residence. Each of these three models was then compared to a null model with no clustering of individuals by likelihood ratio tests.

The next step was to select variables that were most predictive for therapy dropout out of the large number of variables available. The method used for this selection was the LASSO (Tibshirani, 1996). The LASSO is a modified type of least squares regression that puts a constraint on the sum of the absolute values of the model parameters. In order to do so, it penalizes the coefficients of the regression variables with a regularization parameter *lambda* shrinking some of the coefficients to zero. Variables that still have non-zero coefficients after the regularization are selected to be part of the model. To choose the preferred model, i.e. *lambda*, a cross-validation is performed (James, Witten, Hastie, & Tibshirani, 2013).

The advantages of the LASSO method in comparison to conventional selection procedures, such as the stepwise model selection, are that it reduces the sample dependency during variable selection and prevents multiple comparisons. The latter would require control of the familywise error rate which, especially in the case of large numbers of variables being tested, leads to highly reduced statistical power. The LASSO method, on the contrary, is specifically designed for feature selection in high-dimensional datasets, i.e. datasets with a large number of possible predictors that are analysed compared to the sample size (Brink-Jensen & Ekstrøm, 2014).

For this study, the LASSO was implemented with the R package GLMNET (Friedman, Hastie, & Tibshirani, 2010). Due to the dichotomous nature of the dropout variable, a binomial family model was applied with dropout as the response vector. The input matrix consisted of all potential predictors recorded (compare Table 1). In addition, all interval-scaled variables except the registration year, i.e. age, number of children, posttraumatic symptom severity, depression, anxiety, quality of life, and treatment credibility, were centred, squared, and then entered in the input matrix to test for possible quadratic relationships. The squared registration year was not included due to the lack of a rational that this variable would predict dropout. In total, 25 variables were entered, 12 from the socio-demographic, 10 from the psychological, and three from the treatment-related domain (see introduction).

After obtaining a sequence of models with GLMNET, the choice of *lambda* was based on 10-fold cross-validation minimizing the binomial deviance. All models between the *lambda* minimizing binomial deviance, and the *lambda* of the most regularized model such that the deviance is within one standard error of the minimum, were compared with likelihood ratio tests. This was done to finally find the optimal *lambda* assuming that the most parsimonious model should be chosen if a set of models do not differ significantly in their model fit, i.e. enforcing a principle of sparsity.

If coefficients obtained from a LASSO shall be compared with coefficients found in other studies, these are required to include the exact same variables as possible predictors. This is due to the fact the final LASSO model (i.e. its regularization parameter *lambda* and the coefficients) depends on all the input variables, even though some of them may be shrunk to zero. However, a completely identical variable set in comparison studies is highly unlikely. Hence, the predictor variables identified from the LASSO were entered into a logistic regression. For this model, variable coefficients and odds ratios were determined.

Hosmer, Lemeshow, and Sturdivant (2013) recommend classification rates of the selected model as a true measure of fit by which its prediction accuracy could be evaluated. Furthermore, the Area Under the Receiver Operating Characteristic Curve (AUC), implemented with the R package ROCR (Sing, Sander, Beerenwinkel, & Lengauer, 2005) was determined which assessed the model's ability to discriminate between participants who drop out of treatment and those who do not. As a rule of thumb, the following guidelines to the values of the AUC can be applied: AUC = 0.5 no discrimination, 0.5 < AUC < 0.7 poor discrimination, 0.7 ≤ AUC < 0.8 acceptable discrimination, 0.8 ≤ AUC < 0.9 excellent discrimination, and AUC ≥ 0.9 outstanding discrimination (Hosmer et al., 2013). For comparability reasons, the logistic regression model was used for the classification rates and the AUC.

3. Results

3.1. Analysis of the influence of countries of origin and countries of residence on dropout

In total, 37.3% of the participants dropped out. Likelihood ratio tests showed that the random-intercept models with the clustering of participants in countries of origin and countries of residence, respectively, did not implicate better model fits to the data than a null model with no clustering of individuals ($\chi^2_{(1)} = 0.61$, $p = .44$, and $\chi^2_{(1)} = 2.94$, $p = .09$, respectively). The cross-classified model including the clustering of participants in countries of origin *and* in countries of residence also did not prove superior ($\chi^2_{(2)} = 2.61$, $p = .11$). Hence, the single-level model was adopted. This implied that dropout did not vary significantly between clients from different countries of origin or from different countries of residence nor did it vary significantly between clusters of individuals with the same country of origin *and* the same country of residence (cross-classified model).

3.2. Variable selection for the dropout prediction model with LASSO

Out of the 25 variables entered (see Statistical Analysis), the LASSO yielded a model with three predictors that minimized binomial deviance and enforced sparsity (Figure 1). These predictors and the direction of the relationship to treatment dropout were as follows: The probability of dropout was predicted by year of registration (i.e. earlier years of registration predicted lower dropout probability), marital status (i.e. divorced participants' predicted probability to drop out was higher compared to non-divorced, i.e. single, married, or widowed, clients), and treatment credibility scores (i.e. higher predicted dropout probability of participants with lower treatment credibility; Tables 2 and 3).

The inclusion of the variables gender, age, number of children, education, migration status, posttraumatic symptom severity, type of trauma, depression, anxiety, and quality of life did not improve the model fit because it implied higher binomial deviance values (compare Figure 1(b)) and thus could not enhance the precision of predictions of dropout. The same applied for the inclusion of the centred and squared variables age, number of children, posttraumatic symptom severity, depression, anxiety, quality of life, and treatment credibility.

The coefficient of the variable marital status (divorced) would be the first shrunk to zero with increasing values of lambda starting from *l. min* = 0.0333 (see Statistical Analysis and Figure 1(a)). Therefore, in order to enforce sparsity, a likelihood ratio test was performed comparing the model with the three selected variables year of registration, marital status (divorced), and treatment credibility, with the more restricted model with only two predictors excluding the variable marital status (divorced). The likelihood ratio test showed that the three-predictors-model significantly improved the model fit compared to the two-predictor-model ($\chi^2_{(1)} = 6.68$, $p = .01$), it was therefore selected for the further analyses.

3.3. Generalized linear model for dropout prediction

Entering the predictor variables identified with the LASSO into a conventional logistic regression model yielded the same pattern of relationships to treatment dropout as the LASSO-derived model. The coefficient values slightly differed (Table 2).

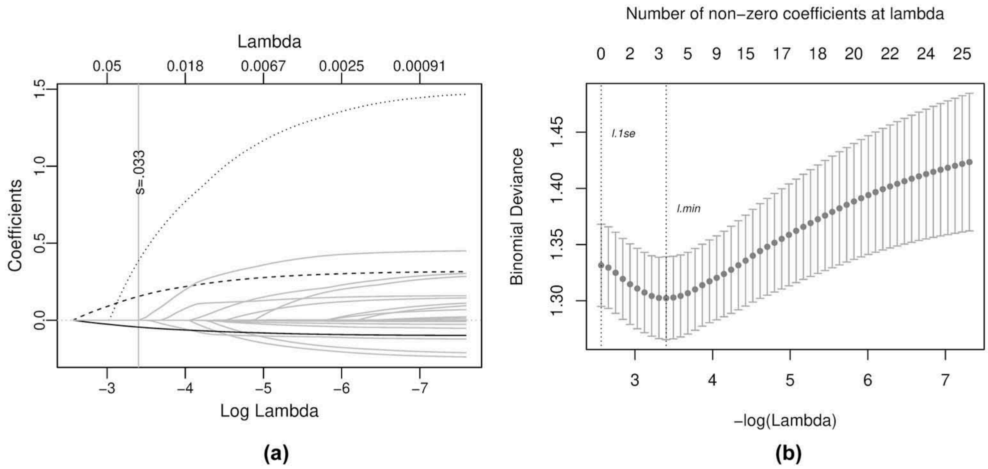

Figure 1. LASSO (Least Absolute Shrinkage and Selection Operator) plots generated in GLMNET. (a) Variable fit. Each curve represents a variable in the full model prior to optimization. Curves show the path of each variable's coefficient as *lambda* varies. *s*= 0.033 corresponds to the optimal *lambda* identified after cross-validation (*l.min*). Selected variables: dashed = year of registration, solid = treatment credibility, dotted = marital status (divorced). See supplemental material for the figure with all variables labelled. (b) Non-zero variable fit after 10-fold cross-validation which evaluates the binomial deviance associated with each *lambda*. Values are cross-validated means of binomial deviance, with standard errors represented by vertical bars. *l.min* corresponds to the *lambda* that minimizes deviance. *l.1se* corresponds to the *lambda* of the most regularized model such that the deviance is within one standard error of the minimum.

Table 2. Non-zero coefficients from LASSO regression and results of the logistic regression of pre-selected predictors on treatment dropout versus completion.

		Logistic regression			
			95% CI for odds ratio		
Variable	LASSO-derived coefficient	*B* (SE)	Lower	Odds ratio	Upper
Constant	− 0.99	− 1.50 (0.30)**			
Year of registration	0.15	0.31 (0.09)**	1.14	1.36	1.63
Marital status (divorced)	0.39	1.27 (0.49)*	1.37	3.58	9.70
Treatment credibility (CEQ)	− 0.04	− 0.09 (0.03)**	0.87	0.92	0.96

N = 386. LASSO = Least Absolute Shrinkage and Selection Operator; *B*= Logistic regression coefficient; SE = standard error; CI = confidence interval; CEQ = credibility/expectancy questionnaire. Positive coefficients imply higher predicted dropout probabilities with increasing variable values, negative coefficients imply lower predicted dropout probabilities with increasing variable values. Logistic regression model $\chi^2_{(3)} = 26.48$, $p < .001$. * *p < .01*, ** *p < .001*.

Table 3. LASSO-selected variables of dropouts versus completers.

	Completers	Dropouts
Variable	%, *M*	%, *M*
Year of registration (%)		
2013 [a]	79.3	20.7
2014	68.9	31.1
2015	70.2	29.8
2016	64.5	35.5
2017	54.7	45.3
2018 [a]	33.3	66.7
Marital status (%)		
Divorced	45.0	55.0
Non-divorced (single, married, or widowed)	63.7	36.3
Treatment credibility (CEQ; *M*)	19.78	18.35

N = 386. LASSO = Least Absolute Shrinkage and Selection Operator; M = mean; CEQ = credibility/expectancy questionnaire.
[a]Participants were recruited from May 2013 to January 2018.

3.4. Classification rates and discriminative ability of the selected model

The selected three-factor-model predicted treatment dropout or completion correctly in 65.5% of the cases when assuming a cutpoint of 0.5, with a sensitivity of 25.0% and a specificity of 89.7% (see Table 4). Given the dropout rate of 37.3%, this sensitivity value means that prediction of dropouts is worse than chance, however, looking at the specificity, the three-factor model enhanced the prediction of completers. A null model based on the assumption that no client drops out would result in a total prediction accuracy of 62.7%. Thus, the selected logistic regression model did not substantially improve the overall prediction accuracy. This conclusion was verified by the value of the AUC of 0.652. According to the rule of thumb (Hosmer et al., 2013; see Statistical Analysis), this showed merely a poor ability of the model to discriminate between treatment dropout and completion.

4. Discussion

This study set out to identify predictors of treatment dropout in psychotherapy by analysing a large variety of socio-demographic, psychological, and treatment-related factors. The overall dropout rate of 37.3% observed lies slightly above the range of mean dropout rates identified by meta-analyses for psychotherapy

Table 4. Classification table based on the selected logistic regression model using a cutpoint of 0.5.

		Predicted		
		Dropouts (*n*)	Completers (*n*)	Total (*n*)
Observed	Dropouts	36	108	144
	Completers	25	217	242
	Total	61	325	386
	% correct	59.0	66.8	65.5

N = 386. Sensitivity: 25.0%; Specificity: 89.7%.

dropout in general (Fernandez et al., 2015). However, it is comparable to the rate van Ballegooijen et al. (2014) found for internet-based interventions for depression (34.9%) and well within the range identified for PTSD-specific internet-based therapies by Kuester et al. (2016; i.e. 0–54%) and Simon et al. (2019; 8.7–62.5%). Thus, it confirms findings of higher dropout rates for internet-based compared to face-to-face-interventions. In addition, the rate is in line with the dropout rate found for trauma-focused cognitive-behavioural therapies for PTSD which is much higher than for non-trauma-focused therapies for PTSD (meta-analysis, Imel et al., 2013). However, it should be noted at this point that the extent of clinical attention placed on the trauma is not a primary reason for treatment dropout (Imel et al., 2013)

It was shown that dropout rates did not vary significantly between participants from different countries of origin or from different countries of residence. Likewise, dropout did not vary significantly between clusters of individuals with the same country of origin and the same country of residence, i.e. the same migration path. To the author's knowledge, this is the first study of psychotherapy dropout in a treatment programme that is implemented simultaneously in different countries. Therefore, this result cannot be related to other research. It suggests that country-specific processes such as, for example, intercultural differences or distinct societal developments, do not play a predominant role in the processes underlying treatment dropout.

Three of the 25 variables tested led to a slightly enhanced prediction accuracy (65.5%, compared to 62.7% accuracy of a null model). These variables were the year of registration (earlier years of registration predicted lower dropout probability), the marital status (divorced participants' probability to drop out was higher compared to non-divorced, i.e. single, married, or widowed, clients), and the treatment credibility scores (higher dropout probability of participants with lower treatment credibility). Sensitivity and specificity values show that the accuracy enhancements of the three-factor-model are based on better accuracy of the prediction of completers rather than of dropouts.

The higher probability to drop out of divorced participants compared to all other clients is, at first sight, in line with previous findings that existing relationships are a protective factor against dropout (Swift & Greenberg, 2012). However, two of the three other categories of marital status, i.e. single and widowed, also imply the absence of a relationship but were not associated with higher dropout probability. Melville et al. (2010) already pointed out that partners can be a source of social support as well as of stress. Participants who are married may or may not perceive their relationship as supportive for psychotherapy, depending on how their spouses engage emotionally and how they react to that (Tarrier, Sommerfield, & Pilgrim, 1999; Wang, Küffer, Wang, & Maercker, 2014). Their marital status, therefore, does not necessarily impact their dropout probability in one way or the other. The case of divorced participants may be different, however. According to Buchbinder and Abu Tanha (2019), divorce is seen as a deviation in Arab society and can have severe consequences, especially for women. Studies have found various social and psychological consequences such as decreased socioeconomic status, restricted personal freedom, more depression, and less satisfaction with life (Al-Krenawi & Graham, 1998, 2004; Shah, 2004). It should be highlighted that conclusions from individual studies about implications of a divorce to entire Arabic-speaking populations must be drawn with great care. However, against the background of the relatively large difference between dropout rates of divorced versus non-divorced clients found in this study, it seems plausible that the high emotional distress coming along with the consequences of divorce described above may be an explanation for the increased dropout risk.

The second predictor identified, the year of registration, seems to be more difficult to explain. The underlying causes might be attributed to technical factors specific for internet-based interventions. Technology has been shown to play a role for adherence and dropout in online interventions (Donkin & Glozier, 2012; Kelders, Kok, Ossebaard, & Van Gemert-Pijnen, 2012). For this programme, the information technology and design of the intervention examined is based on a set-up developed in 2013. The online platform is not adjusted for smartphone use but only for PCs. This is especially relevant as the treatment programme consists of extensive writing assignments. Even though smartphone use in Arab countries lies below the global average, it grows very rapidly (GSMA, 2013, 2018). Taken together, these constantly growing discrepancies between the design and the technology of the treatment programme and the expectancies and usage patterns of participants may have led to the rising dropout rates.

The third predictor identified was the treatment credibility, with higher dropout probability of participants with lower credibility scores. This association has not yet been found in previous quantitative studies. However, qualitative research has identified factors that are consistent with it such as participants' perception of the worth of an intervention (Donkin & Glozier, 2012) or the identification with a programme and a belief that it was applicable to one's individual situation (Gerhards et al., 2011).

In this study, we could not identify further significant predictors for treatment dropout. This reflects the already existing inconsistent literature, e.g. with regard to education or psychopathology. However, the lack of evidence for age and gender as predictors deviates from previous meta-analyses (Melville et al., 2010; Swift & Greenberg, 2012). It could be assumed that the dropout predictors in this cohort may be different in general, since the participants had almost exclusively this therapy available, because in their places of residence psychotherapeutical support is missing (e.g. in war zones) or too expensive or they are not allowed to go to a therapist without accompaniment. In addition, we assume that in our study the sample did not vary much with regard to the years of age (M = 26.00, SD = 6.00).

4.1. Limitations

One of the fundamental problems of research on psychotherapy dropout which also applies for the present study is the lack of post-treatment data of dropouts (i.e. participants who failed to progress past the fourth writing assignment). Even though treatment outcomes of dropouts are most often poorer than those of completers, there are also examples where a lack of difference in treatment outcomes was found (e.g. Lester et al., 2010). Thus, the possibility of an early recovery of clients before dropping out must always be kept in mind. In addition, we did not explicitly and systematically assess adverse events during treatment or reasons for dropout. Therefore, we were not able to report potential events which influence dropout or continuation but are crucial for future studies. At this point, however, we would like to point out a few reasons which might be responsible for the high dropout rate. From the RCT we have hints that technical problems could be a reason. The main issue here is a stable Internet connection, which is often interrupted in current war zones. Permanent respect for privacy could also be a reason for discontinuing treatment. We assume that many patients share the computer with other family members. Often there is a lack of privacy and participants terminate the treatment prematurely out of fear that family members find out they receive treatment. The therapeutic approach of trauma exposure should also be mentioned. It has been shown that in the internet-based context this technique has comparatively high dropout rates (Imel et al., 2013). A last point is the potential improvement of symptoms might be a reason for dropout (e.g. Van Minnen & Foa, 2006). Therefore, it should be recorded at this point in the future what was decisive for the termination.

Another limitation of this study concerns the multilevel analyses of the influence of countries of origin and countries of residence on dropout. Of the 35 countries, which were considered in these analyses, there were some countries such as Egypt with almost 100 participants and others such as Libya with only six clients. No clear-cut rules about the homogeneity and sizes of samples in multilevel logistic models exist (Schoeneberger, 2016), but especially the small samples could have led to biases in the estimations of parameters (Moineddin, Matheson, & Glazier, 2007). The results of the analyses of the influence of countries on treatment dropout should, therefore, be interpreted with caution and verified in further studies.

Furthermore, it must be acknowledged that the association found between the marital status (divorced) and a higher dropout probability, albeit significant, is based on very few participants: Only 5.2% of the sample population, i.e. 20 participants, were divorced. Thus, this finding needs to be verified in further studies with larger (sub)sample size.

Additionally, the sample was not representative with regard to the Arabic-speaking population. The sample consisted of young and well-educated participants. It seems that internet-based interventions are more likely to appeal to individuals with a higher level of education (e.g. meta-analysis of interventions for arabic-speaking adults, Kayrouz et al., 2018). The very young age is not reflected to this extent in other interventions with Arabic-speaking participants or in the context of internet-based treatment and seems to be a special feature of this sample (also shown in the RCT, Knaevelsrud et al., 2015). With reference to the corresponding country-specific age pyramids, this sample reflects the age distribution quite well (e.g. Egypt). The current study was an open-label dissemination study and therefore used a different design as the studies included in meta-analysis for dropout and efficacy. However, this study did not aim to be an efficacy trial requiring randomized controlled allocation. A major advantage of the study is that it has a sufficient sample size and the intervention is offered in a practical context. Nevertheless, the limitation of the study design should be noted.

5. Conclusions

The study shows how difficult the prediction of psychotherapy treatment dropout is. Only three of 25 variables facilitated the prediction of dropout and the ability of the resulting model to discriminate between dropout and completion was still just poor. On the one hand, that might reflect the inconsistent findings of dropout predictors in the literature. On the other hand, it might be crucial to include variables at baseline which detect potential change mechanisms in psychotherapy including ability of resource activation, problem actuation, clarification of meaning and mastery as well as therapeutical alliance (Mander et al., 2013).

The closer inspection of the three identified variables does offer some insights about risk factors of dropout that can be used in future research and practice. Given the higher probability of divorced participants to drop out this group should be given special attention in psychotherapy programmes although this results should be interpreted with caution due to the small subsample of divorced participants in this study.

Growing discrepancies between the design and technology of the treatment programme and the usage patterns of participants seem to be plausible factors explaining the rising dropout rates in the analysed time. Such technological variables are specific to online interventions and show that findings from face-to-face therapy research cannot simply be transferred unmodified to internet-based programmes. In practice, online interventions must face the challenge of constantly staying 'up to date' with their design and technology.

The higher dropout probability of participants with lower treatment credibility scores emphasizes the importance of the very initial phase of therapy programmes. At this stage, before even starting the programme, the rationale of the therapy is explained, and the clients' beliefs about its credibility can possibly be influenced positively. Participants who are more convinced that the programme is trustworthy and can help them would then be more motivated to persist and finally benefit from the completion of the therapy. In addition, the credibility of internet-based psychotherapy should be improved, for example, by further enhancing transparency about programmes' contents and modes of action, by broader dissemination of research results, or by quality management through standardized certification.

Nevertheless, given the poor prediction accuracy of this three-factor-model, it must be concluded that predicting treatment dropout in psychotherapy continues to be a challenging endeavour with heterogeneous results, even though the present study already included 25 variables and applied an innovative and adequate statistical method. It may be very important to look at each psychotherapy intervention individually when investigating dropout. Two of the three variables identified in the predictor analysis, i.e. the year of registration and the treatment credibility, represent the treatment-related domain. The third variable, the marital status, possibly had a very particular relevance in the target group of an Arabic-speaking population and represents the only predictor from the socio-demographic domain. Psychopathology, as the third domain, had no impact on dropout rates. Meta-analytical results showed a correlation between the severity of psychopathology and dropout (i.e. low severity of diagnosis, Kuester et al., 2016; Melville et al., 2010). This could not be found. One assumption is the very high general severity of symptoms in the sample of both PTSD and depressive symptomatology, which could potentially prevent the identification of psychopathology as a predictor.

From the theoretical standpoint with regard to the poor model of discrimination, it is likely that only if treatments are analysed in detail, such specific predictors can be detected and identified for further analysis or programme enhancements. Thus, this study seems to underline the difficulty of previous studies to identify general and common predictors of treatment dropout.

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ORCID

Christine Knaevelsrud http://orcid.org/0000-0003-1342-7006

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