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Predicting Spider Fear from Questionnaire and Rating Data Using Machine Learning

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Sophia Shea, BSc

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Abstract

The fear of spiders is very widespread in our population and belongs to one of the most common specific phobias. It is a threat of wellbeing to affected individuals. The current main treatment for spider fear is exposure therapy, in which patients are confronted with their feared stimuli. Exposure therapy is very time-consuming, shows high drop-out rates, and affected individuals mostly do not seek help. To address these limitations, we aim at developing a machine learning model which can predict image-based fear ratings in individuals. This would be a first step in developing automized and individualized exposure therapy, which could further be adapted in computer-based exposure therapy.

Two comparable studies were conducted, in which spider-fearful individuals rated images of spiders on a continuous scale according to subjective fear. A light gradient boosted machine (LightGBM) regression was chosen to predict our target, the subjective fear individuals of the second study experienced while viewing spider images. We used fear ratings and questionnaire data of our first study to train the machine learning model. A fear mean per stimulus was calculated from a holdout set of our first study and used as a model predictor. Further, questionnaire and demographic data of our second study were inserted into the model as predictors. The results indicate that fear mean was the most important predictor. Additionally, the sum scores of the Fear of Spiders Questionnaire, State Trait Anxiety Inventory – state, Fragebogen zur Erfassung der Ekelempfindlichkeit (disgust propensity scale), and Spinnenangst Screening (spider fear screening) were important predictors. We were able to explain 26 percent of the variance of participants' subjective fear ratings. Our approach is a new step toward personalized exposure therapy and might have the potential to address the limitations and challenges of conventional exposure therapy. Directions for further research which could make automatized and individualized exposure therapy feasible in the near future are given.

Zusammenfassung

Die Angst vor Spinnen ist in der Bevölkerung weit verbreitet und gehört zu einer der am häufigsten auftretenden spezifischen Phobien. Das Wohlbefinden der betroffenen Personen wird deutlich eingeschränkt. Die momentan dominierende Behandlungsmöglichkeit ist die Expositionstherapie. Hierbei werden Patient:innen mit furchtauslösenden Stimuli konfrontiert. Expositionstherapie ist sehr zeitaufwendig und viele Betroffene nehmen keine Behandlung in Anspruch. Um diese Limitationen zu adressieren ist es unser Ziel, mittels maschinellen Lernens ein Modell zu entwickeln, das die individuelle Furchtbewertung von Spinnenbildern vorhersagen kann. Dies könnte ein erster Schritt sein, automatisierte und individualisierte Expositionstherapie zu entwickeln, welche zusätzlich Potential in computerbasierter Expositionstherapie hätte.

Zwei vergleichbare Studien wurden durchgeführt, in welchen Proband:innen mit Spinnenangst ihre subjektiv empfundene Furcht beim Ansehen von Spinnenbildern auf einer kontinuierlichen Skala bewertet haben. Eine Light Gradient Boosted Machine (LightGBM) Regression wurde verwendet, um unsere Zielvariable vorherzusagen: Subjektives Furchtempfinden von Proband:innen der zweiten Studie beim Ansehen von Spinnenbildern. Dazu dienten Furchtbewertungen und Fragebogendaten der ersten Studie als Modellprädiktoren, sowie Fragebogen- und demografische Daten der zweiten Studie. Ein Furcht-Mittelwert pro Spinnenbild wurde mit Daten der ersten Studie berechnet und als Prädiktor verwendet. Unsere Ergebnisse zeigen, dass dieser Furcht-Mittelwert der wichtigste Prädiktor war. Zusätzlich waren die erzielten Gesamtpunkte des Fear of Spiders Questionnaire, des State Trait Anxiety Inventory – state, des Fragebogen zur Erfassung der Ekelempfindlichkeit und des Spinnenangst Screening wichtige Prädiktoren. Unser Modell konnte 26 Prozent der Varianz von subjektiven Furchtbewertungen erklären. Dieser Ansatz ist ein wichtiger Schritt für zukünftige personalisierte Expositionstherapie und hat möglicherweise das Potenzial, die Limitationen konventioneller Expositionstherapie zu adressieren. Anregungen für weitere Forschung, die automatisierte und individualisierte Expositionstherapie in greifbare Nähe rückt, werden diskutiert.

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Introduction

Fear occurs as a protection to the risk of harm and prepares us to deal with danger. It triggers physiological, behavioral, cognitive, as well as experiential responses (World Health Organization, 2018). Therefore, fear poses a threat to people's well-being. The International Classification of Disease (ICD-11) distinguished the two terms fear and anxiety from each other: Fear is classified as an emotional response to perceived imminent threat or danger associated with urges to flee or fight. Anxiety is defined as apprehensiveness or anticipation of future danger or misfortune accompanied by a feeling of worry, distress, or somatic symptoms of tension. The focus of anticipated danger may be internal or external (World Health Organization, 2018). Fear is a rather short lasting, defensive response to a present threat, while anxiety is understood as a more sustained preparatory response to situations in which a threat might occur (Davis, 2006).

Fear of spiders

According to the ICD-11, fear of spiders is an anxiety or fear-related disorder and belongs to the subgroup of specific phobias. The classification system characterizes fear of spiders by a salient fear or anxiety which occurs through exposure or anticipation of exposure to spiders, for example the proximity to a spider, which is inconsistent with the actual danger of it. Patients are faced with intense fear or anxiety or are avoidant (World Health Organization, 2018). To be classified as a phobia in the ICD-11, symptoms must be present for at least several months and result in severe distress or impaired everyday functioning. For people diagnosed with a specific phobia such as arachnophobia, the phobia of spiders, fear is pathological and interferes with everyday functioning (World Health Organization, 2018). Cisler et al. (2009) claim that fear and anxiety are the two main emotions in fear of spiders. A third emotion, disgust, is suggested (Leutgeb & Schienle, 2012a; Cisler et al., 2009). Several studies demonstrate that disgust and fear of contamination play a crucial role in spider phobia (de Jong et al., 2000; de Jong et al., 2002), and participants with clinical spider fear seem to show stronger disgust sensitivity than non-phobic participants (Mulkens et al., 1996).

Spider phobia shows a particularly early age of onset (Boyd et al., 1990). With a 12-month prevalence of 6.4%, specific phobias are the most widespread anxiety disorder (Wittchen et al., 2011). Furthermore, according to Oosterink et al. (2009), spider phobia is the third most common specific phobia with a point prevalence of 2.7%. Comorbidity is frequently associated with specific phobias, especially with further anxiety and depressive disorders (American Psychiatric Association, 2013). Additionally,, anxiety disorders in general are associated with high rates of treatment dropout

and recurrence (Fernandez et al., 2015; Scholten et al., 2012).

Treatments

The most common spider phobia treatments are behavioral approaches (Davey, 2007) such as exposure (Wolitzky-Taylor et al., 2008). Several limitations of in vivo exposure therapy are addressed by computerized exposure (Dewis et al., 2001). According to a recent review and meta-analysis, medication currently seems to be insufficient in treating phobia (Steenen et al., 2016).

Exposure Therapy. Exposure therapy (ET) is the gold standard treatment for specific phobias, including spider phobia (Wolitzky-Taylor et al., 2008). The proposed mechanism behind ET is that patients' experienced fear diminishes due to confrontation with the feared stimulus. Therefore, in spider phobia, patients are deliberately confronted with a spider to reduce their fear, as well as their avoidance behavior. This process of reducing responsivity is called habituation (Brady & Raines, 2009). According to Craske et al. (2014), extinction learning, and inhibitory learning are proposed to be mechanisms of ET besides habituation. In their paper, extinction is described as the process by which an association is unlearned. Inhibitory learning is proposed to help the process of extinction by recognizing that an aversive event does not always occur when the feared stimulus is encountered (Craske et al., 2014).

ET is well-evidenced and often used in treatment for several avoidance behaviors (Healey et al., 2017). It has broad effects in adults, as well as in children with spider phobia (Leutgeb et al., 2012b; Wolitzky-Taylor et al., 2008). Responses to the feared stimuli can range from mild anxiety to pronounced panic symptoms. Hence, therapists make use of diverse material to engineer experiences, in which various levels of anxiety are induced, e.g., images or videos with varying species or sizes of spiders. Importantly, therapists need material to escalate an exposure as the therapy progresses. In a potential automized ET, an algorithm needs this as well (Richard & Lauterbach, 2011).

Numerous variations of ET exist, and the execution is often not sufficiently standardized, based on "best practice" (Richard & Lauterbach, 2011). Single session and repeated exposure approaches, prompt (flooding) and gradual approaches, in vivo and imaginative/virtual approaches, group, and individual therapy. One-session ET, in which patients are gradually exposed to fearful stimuli for up to three hours, has been found effective to treat specific phobias (Miloff et al., 2016; Li et al., 2020; Müller et al., 2011). In vivo exposure involves the confrontation with the object or situation in real life (for example, touching a real spider). This approach consistently leads to high

success rates and is considered superior to the approaches mentioned above (Wolitzky-Taylor et al., 2008). Li et al. (2020) conducted studies in an Australian museum, using spider exhibits, showing that one-session ET in groups of 15 individuals is effective as well, resulting in significantly reduced fear and avoidance toward spiders that were comparable to individual and small group one-session outcomes of previous studies. This novel approach is a feasible and resource-effective method to treat spider phobia.

Several factors have been found to influence the success of ET. Daytime may affect ET efficiency in spider phobic individuals, as the effects of ET have been shown to be stronger through high endogenous cortisol levels in the morning compared to lower levels in the afternoon (Lass-Hennemann & Michael, 2014). Further positive effects for the efficiency of ET include low trait anxiety, since higher trait anxiety scores lead to less success of in vivo ET and are associated with increased risk of returned fear (Muris et al., 1998; Rodriguez et al., 1999). In addition, high motivation, high self-efficacy, and evoking disgust in addition to anxiety have been found to be crucial traits for ET success (St-Jacques et al., 2010; Zoellner et al., 2000; Matthews et al., 2014). The review by Böhnlein et al. (2020) conclude that relaxation can limit the effectiveness of ET, while focusing on cognitive changes, context variation, sleep, and memory-enhancing drugs seem to have positive effects on treatment outcome. Although ET is highly effective, it is infrequently exhibited in routine clinical care due to issues of practicability (Ihmig et al., 2020).

Computerized Therapy. Despite several established treatments, only 31% of individuals meeting DSM criteria for phobia sought treatment in the investigation of Regier et al. (1993). Personal reasons of individuals with phobia include an unwillingness to confront the feared stimuli and not being aware of existing treatments (Magee et al., 1996). Besides this, logistic challenges of ET occur in the accessing, collecting, storing, and/or maintaining stimuli, in this case, spiders (Miloff et al., 2016). Clinicians may also avoid implementing ET due to fear of it causing harm or being unbearable for patients (Meyer et al., 2014). Computerized therapy makes use of images or videos of the feared object or situation, which are viewed by the patient on a screen (Wolitzky-Taylor et al., 2008). Some computerized therapy approaches have the potential to facilitate access, decrease costs and effort, and increase acceptability and effectiveness (Bouchard et al., 2006).

Computerized Exposure. Although in vivo exposure is the first-line treatment for specific phobias, a current meta-analysis suggests that virtual reality exposure therapy (VRET) is as effective as in vivo exposure (Carl et al., 2019). In addition, VRET is a widely accepted treatment for specific phobias and anxiety disorders (Botella et al., 2016; Lindner et al., 2020). According to Lindner et al.

(2020), the fear reduction achieved by VRET generalizes to real-world stimuli. In the randomized controlled trial by Botella et al. (2016), participants of the augmented reality condition significantly improved on all outcome measures, while on average yielding less improvement than participants of the in vivo condition. Yet, these differences diminished at three- and six-months follow-up. Furthermore, participants of the in vivo condition considered the treatment more useful for reducing their phobia, whereas participants of the augmented reality condition perceived the treatment as less aversive. Multiple studies on virtual reality/virtual augmentation ET approaches for spider fear treatment have revealed large, significant reductions in behavioral avoidance and subjective fear after treatment. The computer-aided exposure by Dewis et al. (2001) showed reductions in phobic symptomatology. Participants improved significantly from pre- to post-treatment and pre-treatment to follow-up. Further, the results of Miloff et al. (2019) were comparable to the non-VRET group for the 3- and 12-months follow-up, but significantly smaller for the 12-months follow-up. Importantly, there were no significant differences in negative treatment effects. Lindner et al. (2020) examined user experience for this gamified and automated VRET for spider phobia. The results indicate that the automated and gamified format was perceived as natural, clearly transporting the psychotherapeutic goal behind it. Disadvantages included only such that have been named for in vivo ET as well, for example the distressing nature of ET (Silva et al., 2011). Since VRET can be automated and therefore potentially replace a therapist with gamification elements, it might be a valuable approach in closing the treatment gap for anxiety disorders and phobias (Lindner et al., 2020). Further advantages of VR may include prolonged exposure, since it establishes a fictitious, safe, and controllable situation, which may increase emotional engagement and acceptance (Botella et al., 2015). The current literature also addresses the limitations of VRET. According to Botella and colleagues (2015), challenges include therapists' limited accessibility to systems based on VRET, and lack of training in the use of this approach. Additionally, more cross-cultural studies, to assess the generalizability of the therapy effects, as well as long-term follow-ups are needed (Botella et al., 2015).

Models of Fear

Over the decades, several models have been proposed to explain fear. These conventional models of fear try to find various explanations in the human mind and body for fearful reactions, as well as the development of phobia. Some current models of fear have made it their task to develop models that succeed in helping individuals overcome their fear or phobia (e.g., Hahn et al., 2015; Bălan et al., 2019). A method that has become popular for this purpose is machine learning.

Conventional Models of Fear

Seligman (1971) attempted to explain the origin of fear and the rise of phobias in the population. His theory challenged the classical conditioning approach concerning phobias. According to Seligman (1971), phobic fears differentiate themselves from other fears by being learnt remarkably easy (Seligman, 1971). While past research has relied on Seligman's theory of prepared learning, recent research mainly relies on a bio-psycho-social theory to explain phobic disorders (Hinze et al., 2021). The bio-psycho-social model combines especially genetic and cultural factors. Therefore, this theory is superior in explaining, for example, why the heritability in animal fear is estimated to be about 45% (Van Houtem et al., 2013).

One model attempting to explain phobic behavior is the cognitive-motivational theory, which suggests a hypervigilance-avoidance pattern in patients. According to this hypothesis, phobia patients initially direct their attention to the fear stimulus, before avoiding it (Pflugshaupt et al., 2005). Avoidance helps people to reduce anxiety by reducing encounters with fear-related stimuli. As a disadvantage, avoidance can prevent habituation to, or objective evaluation of these fear related stimuli, which results in maintaining phobia (Mogg et al., 1997). Numerous eye-tracking studies have confirmed the hypervigilance-avoidance hypothesis in spider phobic patients (Pflugshaupt et al., 2005; Hermans et al., 1999; Rinck & Becker, 2006). Participants at first directed their gaze toward the spider, but subsequently exhibited visual avoidance.

Machine Learning Models

Machine learning (ML) is a subfield of artificial intelligence. It can be defined as a computational strategy that automatically learns methods and parameters to optimally solve a problem, without being programmed with a fixed solution by humans. In clinical psychology, the use of ML can be categorized into four purposes: diagnosis, prognosis, treatment prediction, and detecting/monitoring biomarkers (Dwyer et al., 2018).

ML models have been used for a number of causes in anxiety treatment, one of them is predicting how people will respond to a treatment, called treatment outcome prediction. For, instance, Hahn et al. (2015) investigated the potential of fMRI data to individually predict responses to cognitive behavioral therapy in patients with agoraphobia. Their results showed high accuracy in response prediction and therefore underpin the potential of neuroimaging data and ML for clinical interventions. ML treatment outcome prediction studies with behavioral data have been done with various mental health patients (Hilbert et al., 2020; Forsell et al., 2020). For example, cognitive

behavioral therapy outcome in individuals could successfully be predicted by Hilbert et al. (2020) and Forsell et al. (2020), using behavioral data and a combination of ML models. Treatment prediction is only one way to use ML in attempting to treat individuals with phobia.

Predicting Individual Fear Levels with Machine Learning. Research concerning ML fear prediction is still extremely limited in general and in the field of spider fear. Yet, some promising research exists. Bălan et al. (2019, 2020) built a model to treat phobia using sensory and self-reported data. The aim of the model was to automatically estimate fear levels and adapt exposure intensity based on individuals' current affective state. Individuals with acrophobia comprised the sample which was divided into 70% training and 30% test data. Various machine and deep learning techniques, using multiple layers in the network, were used for prediction, as well as EEG and physiological data. Two categorical paradigms for fear level estimation were proposed —a two-level (0—no fear and 1—fear), as well as a four-level (0—no fear, 1—low fear, 2—medium fear, 3—high fear) classification system. In their study of 2019, the Random Forest Classifier, a ML method constructing decision trees during model training to improve the predictive accuracy, produced the best prediction. The F-score, a measure of model accuracy, was high with 89.96% for the two-level, and 85.33% for the four-level fear evaluation system (Bălan et al., 2019, 2020).

Aue et al. (2021) used ML to predict fear responses in spider phobic individuals. For this, they measured diverse somatovisceral, cognitive, and diagnostic factors. The aim of their study was to find out whether the measurement of somatovisceral responses increases the prediction of individual fear responses compared to a model taking only diagnostic and cognitive factors into account. Participants rated subjective fear on a 17-point scale from 0% (no fear) to 100% (extreme fear), with steps of 6.25%, resulting in a quasi-continuous outcome which should be predicted by their model. The somatovisceral responses were registered continuously during the rating. To test the model, 33% of the data was used. The results of their multivariate regression model indicate that diagnostic factors were the main predictor of individual fear ratings. Moreover, their model explains on average 81% of the variance in the fear ratings, with an average absolute error of 0.12, within a fear range of 0 to 1.

The study of Ihmig et al. (2020) used biosignals of 80 spider-fearful individuals as predictors for an anxiety level detection ML model. They classified anxiety into two models, one two-level (low and high), and one three-level (low, medium, and high) model. For the analysis, supervised ML techniques were used, which train an algorithm to estimate a model that predicts outcomes accurately. The accuracy of the two-level classification was 89.8%, while the accuracy for the three-

level classification was 74.4%.

Aim and Purpose

ML has the potential to improve treatment prediction, identifying which input variables are helpful for prediction and which are redundant. According to Hahn et al. (2015), fear predicting ML models could allow for individualized treatments and have the potential of bringing personalized medicine into reach, which is seen as the main goal by Richter et al. (2017). Since exposure-based treatments are not equally effective in all patients, there is a call for more individualized psychotherapeutic treatments (Leehr et al., 2021). Therefore, a ML approach was chosen for our study instead of a classical approach, to achieve a more accurate prediction on an individual basis, and maximized individual treatment success compared to other conventional methods. This would be a first step toward a future individualized, as well as automated treatment approach. To make adaptive ET possible, we not only need an accurate ML model, but additionally a controller, which regulates the stimulus presentation. With an accurate fear prediction ML model and a controller, an adaptive ET approach, in which exposure stimuli are adjusted to the individual fear-level, would be feasible. Automized and individualized ET could have positive effects on treatment seeking, decreasing dropouts, and on avoiding fear over- or underload (Arias, 2021). In the future, a standardized treatment could further be used in a bio- or neurofeedback ET setting, which provides patients with feedback of their physiological state to train them in controlling their fear response individually. In addition, an adaptive ET approach could be used in VRET, or serious games. Eventually, this computerized treatment approach could be used for further phobia disorders.

The purpose of this study was to build a ML model for subjective spider-fear prediction. We wanted to identify whether questionnaire data and image ratings have the potential to predict fear on a continuous scale. For this, we trained our model with data from an internet-based study, in which participants rated images of spiders regarding subjective fear levels and filled out spider-fear-related questionnaires. Subsequently, we used the model to predict fear ratings in individuals of an independent second study with a comparable experimental design. Questionnaire data of individuals participating in the second study, and a calculated fear mean of data from individuals in the first study were used as model predictors. Little research on spider fear has been realized in the field of ML, especially continuous regressions, which gave us reason to conduct this study. It is hypothesized that our ML model will predict accurately reported fear levels when a variety of input factors are considered and when our model is trained with data of independent individuals. Importantly, we expect the fear mean of images to be an important predictor, and due to current literature, the Fear of Spiders Questionnaire (Van Bockstaele et al., 2011; Muris & Merckelbach, 1996). With the

possibility to accurately predict subjective fear levels, adaptive ET would come one step further into reach.

Hypothesis

The ML model with the input of questionnaire and image rating data of spider-fearful individuals can predict spider fear in unrelated individuals on a continuous 100-point scale (Bălan et al., 2019; Eder, 2020).

Methods

Two independent studies with a similar experimental design were conducted. Study 1, to train a ML model, and study two, to test our model regarding the prediction of subjective fear ratings. In study 1, questionnaire and image rating data were acquired. During study 2, questionnaire data was gathered beforehand, fMRI data during the passive viewing of images, and image ratings after completing the fMRI task. Only questionnaire and rating data was analyzed in this study, not the fMRI data. This data was inserted into our Light Gradient Boosted Machine (LightGBM) regression model.

Study 1

Participants

In the first study, 210 individuals participated. Our sample was *n* = 151. Of this sample, 124 participants identified as female, and 27 as male. The age span was 18-45 (M = 24, SD = 5,89). Individuals who were pregnant, had a past or present neurological or psychiatric disorder, a present or past alcohol or drug abuse were not able to take part in the study. Participants with a FSQ score <24 were excluded. Spider phobia was not a requirement; basic fear of spiders was sufficient for participation. Eligibility included self-reported spider fear, as well as at least a B2 German level, normal to corrected-to-normal eyesight, and being in the age group of 18-45. Participants were recruited via a University of Vienna website for study participation, Laboratory Administration for Behavioral Sciences (LABS). Either credits or financial compensation was granted. Informed consent was acquired before the start of the experiment.

Stimuli

The images participants viewed and rated consisted of 314 spider images. These images were mainly collected from websites with images for non-commercial use, with free modification, and no attribution required. Of the 314 images, 26 were self-taken. The depicted images included spiders:

- Of various species
- Of various sizes (small, medium, large)
- Of various textures (smooth, hairy)
- Of various number (one, two, up to 60)
- In various distance to camera (close, half-distant, distant)
- In various environments (nature, civilization, human contact)

- In various realness (real spider, cartoon spider)
- With spider web in image or not
- Eating/capturing other animals or not

Out of this pool of spider images, 95 randomly chosen images were shown to a participant. Neutral images depicting inanimate objects, catch trials, and bogus items were presented between the spider images. An example for a catch trial represents the question "How much fear does this image elicit in you?", with the task of sliding a scroll bar all the way to the end of the scale. An example for a bogus item included answering the question "How many fingers does one hand have?". Each image was presented for three seconds, and images were presented in a randomized order. A small number of images was presented twice; however, only the first rating of an image was used in the analysis.

Figure 1

Examples of Spider Images Viewed and Rated by the Participants.

Note. Different types of spider images that were part of the database are depicted. The spiders in the images differ especially in species, features, distance to camera, and environment they are in. All example images were self-taken.

Measures

Subsequently, after viewing an image, participants had 12 seconds to rate the image on a scale from 0-100. To rate fear, they were asked the following question: “Wie viel Angst löst dieses Bild in Ihnen aus? (“How much fear does this image elicit in you?”). Further, the participants answered the

questions “Wie viel Ekel löst dieses Bild in Ihnen aus?” („How much disgust does this image elicit in you?“) on a scale from 0-100, and “Wie nahe könnten Sie an den abgebildeten Inhalt herankommen, wenn Sie Ihre Aversion überwinden wollten?“ („How close could you approach the depicted content if you were to overcome your aversion?”). Participants rated the last question on a scale from zero meters (touching) to ten meters distance. In the present study, only fear ratings were employed.

The following established questionnaires were used to determine participants’ subjective fear of spiders, disgust propensity and sensitivity, and anxiety. Validated German versions of English questionnaires were employed. In our analysis, the sum scores of the questionnaire data were used. The questionnaires were administered in the following order:

- Fear of Spiders Questionnaire (FSQ; Szymanski & O’Donohue, 1995)
  An 18-item self-report questionnaire to assess spider phobia, originally designed to complement the SPQ. Items of the FSQ might represent the assessed time period more accurately and seems to discriminate phobic from nonphobic individuals more reliably.

- Spider Phobia Questionnaire (SPQ; Watts & Sharrock, 1984)
  Created for measuring distinct dimensions of cognitive-behavioral responsiveness toward spiders in spider phobic individuals. These dimensions include vigilance, preoccupation, as well as coping-avoidance. The questionnaire consists of 43 items, demanding “Yes” or “No” answers.

- Spinnenangst Screening [Spider fear screening] (SAS; Rinck et al., 2002)
  A brief and economic four-item questionnaire assessing spider fear on a six points Likert scale. It can be combined with further longer questionnaires easily.

- State Trait Anxiety Inventory (STAI; Spielberger et al., 1970; Spielberger, 1983)
  A self-evaluation questionnaire which captures fear as a current state, and fear as a personality trait. 20 items on each scale evaluate the intensity and frequency of fear.

- Fragebogen zur Erfassung der Ekelempfindlichkeit [Disgust propensity score] (FEE; Schienle et al., 2002)
  A questionnaire to assess disgust propensity, which may have considerable influence on the development and maintenance of anxiety disorders. It consists of 37 items in total, distributed on five scales: Death, body secretions, hygiene, spoilage, and oral rejection.

- Skala zur Erfassung der Ekelsensitivität [Disgust sensitivity scale] (SEE; Schienle et al., 2010)
  A brief scale consisting of seven items to assess disgust sensitivity. Its association with distinct phobia subtypes needs further research.

- Fear of Spiders Questionnaire (FSQ) follow-up

Participants completed the FSQ pre- and post-study, as well as one week after the study as a follow-up.

Experimental Setup

Study 1 was administered via SoSci Survey (Leiner, 2022). The median completion time was 38 minutes. Beginning the study, participants were welcomed by a brief introduction text. On the consecutive pages, participants confirmed comprehending and agreeing to the study information, and further gave consent to their study participation. As a first measure, participants were asked to provide demographic information: Gender, age, and country they currently lived in. Subsequently, the six questionnaires described above were administered. After completing the questionnaires, 95 images out of a pool of 314 spider images were depicted as rating trials. In the rating trial, participants rated the subjectively elicited fear of the depicted spider image. A small number of images was presented twice. Only the first rating of one image was used in the analysis. Catch trials, bogus items, and neutral images were presented in between. Study 1 ended with thanking the participant for taking part in the study and informing about their credit or financial compensation. Seven days after participation, the participants received a link to the follow-up FSQ, for which they had 24 hours to complete.

Study 2

Participants

In the first part of our second study, 58 individuals participated and filled out the questionnaires. Due to the Covid-19 pandemic, several participants were not able to complete the remaining in-person experiment, and the sample remained at n = 30. Of this sample, 26 individuals identified as female, while four identified as male. The age span was 18-37 (M= 23, SD = 3,79). Subsequently, these participants were screened using the SAS questionnaire (Rinck et al., 2002), and an MRI safety questionnaire. The eligibility criterion determined spider fearfulness, which was operationalized by the sum score of the SAS. Participants were excluded if they indicated under 8 of 24 points on the SAS, and if they were not MRI compatible. They were further not qualified to take part in the study if they were pregnant, had claustrophobia, a past or present neurological or psychiatric disorder, and present or past alcohol or drug abuse. To sign up for study 2, individuals visited a University of

Vienna website for study participation, LABS. Participants with at least a B2 level of German, and with normal or corrected-to-normal eyesight in the age group of 18-45 could sign up, if they had not participated in other similar studies which were excluded by us. Informed consent was obtained before the experiment and financial compensation in the amount of 50€ was given at the end of the study.

Stimuli

Of the 314 images used in study 1, 225 were used in study 2. To decide which 225 images were best, the R package maximin was used to exclude average fear/disgust images, and to keep extreme fear/disgust images. This procedure ensured that the spread of the images was as large as possible. They were presented to the participant in the MR in a random order, viewing the pictures on the bold screen behind the MR through a mirror on the head coil. Neutral images depicting inanimate objects and catch trials were shown between the spider images. Catch trials consisted of a depicted demand to either press the left, middle, or right button of an MR button box the participants were holding during the experiment. The images were depicted for four seconds each.

Measures

The same SoSci Survey questionnaires as in study 1 were administered to study 2 participants before the fMRI passive viewing task. Specifically, the FSQ was administered once before the study and a week after the study as a follow-up. In the days following the passive viewing task, participants subjectively rated the images according to elicited fear, disgust, and approach/avoidance, as described for study 1. Only fear ratings were employed for this study. The 225 images were split up equally into three separate SoSci Survey questionnaires. Participants received the links to the questionnaires one day after the experiment via email and were instructed to complete one questionnaire without a break, while being able to take breaks before starting a new questionnaire. The instructions included the request to complete all questionnaires within 48 hours.

Experimental Setup

The eligibility of individuals who signed up to participate in the study was determined by assessing their MR eligibility and their spider fear, using the SAS questionnaire. If they met all inclusion criteria, participants received a link to fill out all questionnaires mentioned above (FSQ, SPQ, STAI state, STAI trait, FEE, SEE) in SoSci survey. Up to two weeks later, participants underwent a short behavioral approach task at the university, which measured how close they approached a spider in a terrarium, and a short virtual reality task, in which participants decided how far they wanted to unblur images

of spiders. Subsequently, the fMRI experiment took place at the MR Center of the University of Vienna and lasted about 110 minutes. The participant was instructed about the viewing task in the MR and filled out an MRI safety questionnaire. In the MR room, a button box for the catch trials was placed in the participants' right hand. After the participant was settled in the MR, a first resting-state scan took place. During this, participants viewed a white fixation cross on a black background. Sequentially, the five functional scans (the passive viewing task) took place, presenting all 225 spider images and neutral images, which were rated by the participants on the next day. These five scans solely distinguished each other by the different presented images. A fixation point was viewed for two to three seconds during the presented images. In addition, an eye tracker was used to monitor whether the participants' eyes were open and directed at the screen while viewing the images. After the five functional scans, a second resting-state, field map acquisition, and a structural scan took place. At the end of the fMRI experiment, the participant was instructed about the further course of the experiment. During the next three days, the participants rated the subjectively elicited fear of all the prior seen spider images online in SoSci Survey, as the participants of study 1 had done. One week after the fMRI experiment, participants completed the FSQ follow-up via SoSci survey.

Machine Learning Analysis

In our analysis, the questionnaire and image fear rating data of 101 individuals of the first study were used to train the ML model. The remaining 50 individuals of the first study were used to calculate a fear mean per image. In machine learning, linear regression is a predictive algorithm that provides a linear relationship between prediction (*Y*), in our case, fear, and input (*X*), which were the following 12 predictors:

- Fear mean (fear_mean)
- FSQ sum score (FSQ_sum)
- SPQ sum score (SPQ_sum)
- STAI state sum score (STAI_state_sum)
- STAI trait sum score (STAI_trait_sum)
- SAS sum score (SAS_sum)
- SEE sum score (SES_sum)
- FEE sum score (FEE_sum)
- Age
- Gender (gender_1.0)
- Time sum (time_sum)

- DEG time (DEG_time)

The fear mean of the image ratings was calculated based on a holdout set of 50 study 1 participants. Time sum is the total number of seconds it takes a person to complete all questionnaires. DEG time is a factor calculated by SoSci survey, giving malus points for filling out the questionnaire very quickly. The testing output/predicted variable was subjective fear rating of study 2 individuals toward spider images on a continuous scale. Participants rated the images on a scale from 0-100; however, our predictions were assessed on a scale from 1-101, since SoSci survey does not allow predictions starting at 0.

All predictors were arranged into a long format using R version 4.1.3 (R Core Team, 2017), and the integrated development environment for R, R-Studio version 2022.02.1 +461 (RStudio Team, 2016). The data was cleaned, and unused data, such as disgust and approach/avoidance ratings, were excluded by code. One person identifying as diverse was excluded, since gender effects were investigated, and the group of diverse individuals was not large enough for analysis. A LightGBM algorithm was chosen for our model, using nested cross-validation to improve predictive performance of the model, as well as hyperparameter tuning to avoid overfitting and control for model complexity. Measures to evaluate our model performance were R^2 and mean absolute error (MAE).

LightGBM

We made use of the ML subcategory “supervised learning” which has the purpose of training an algorithm to estimate a model that predicts outcomes accurately. It is called “supervised” since researchers provide feedback for the algorithm training by labeling input data (Ihmig et al., 2020). A powerful supervised learning technique is gradient boosting. In our analysis, a LightGBM algorithm was chosen for implementation (Ke et al., 2017; Microsoft Corporation, 2022). Gradient boosting is a ML boosting method with the purpose of creating a more accurate predictive model. It is an ensemble learning technique in which the results of each base-learner are combined to a final estimate. LightGBM is an efficient open-source implementation of the stochastic gradient boosting ensemble that uses tree-based learning algorithms. The algorithm quickens the training process of conventional gradient boosted decision trees while achieving almost the same accuracy (Ke et al., 2017).

The aim of gradient boosting is to find a function which predicts the output feature from the input variables best. This method provides multiple learning algorithms of weak prediction models.

The weak learners of the prediction models are a ML algorithm that produce a slightly superior accuracy than random guessing. The weak learners in our model are decision trees. By combining those weak leaners into one strong learner, LightGBM allows an optimization of the arbitrary differentiable loss function, in our case the mean squared error with L1 norm regularization. The decision trees are combined stepwise into one strong learner. In each tree, a single leaf makes a first initial guess for the fear of all samples. The first guess is the average value. Then, a tree is built that learns how to fit to the residual between the predictions of the first leave and the ground truth. The leaf with maximal delta loss is chosen to grow. Further trees are built on the errors the previous trees made. Trees are grown leaf-wise and best-first. LightGBM limits the maximal depth parameter and the maximal number of leafs to prevents overfitting (Ke et al., 2017).

Nested Cross-Validation. Essentially, nested cross-validation was performed in our analysis. Nested cross-validation is a popular resampling procedure that estimates the predictive performance of a model through the true prediction error, improving model prediction (Hastie et al., 2009). This evaluates the generalizability of predictive models and prevents overfitting while training the model (Berrar, 2018). Nested cross-validation was implemented, since it is capable of selecting the best set of hyperparameters, of estimating model error and hyperparameter search, and preventing overfitting and data leakage. It helps decide which parameters work best for our model (Hastie et al., 2009). Nested cross-validation consists of a double loop. The outer loop assesses the quality of the model, while the inner loop exhibits the model/parameter selection. The number of splits for our inner loop was a fixed value in the range of 25 and 250. The value was computed to make a total of about 10000 predictions per cross-validation iteration.

Hyperparameter Tuning with Bayesian Optimization. Hyperparameter tuning/optimization is a process of choosing a set of hyperparameters for our LightGBM algorithm that is most accurate for our dataset. It controls model complexity and avoids overfitting, since the quality of the model changes when the values of the hyperparameter vary. We chose to implement Bayesian algorithm, a global optimization method. A Bayes search cross-validation object is created for hyperparameter tuning and fitted to the data. The advantages of Bayesian algorithms include less time until an optimal set of parameters is found by minimizing the total number of iterations to reach global optima, and increased generalization performance of the test set (Jones, 2001; Wang et al., 2020). This is achieved by the algorithm running models many times with different sets of hyperparameter values. By considering information on the previous observed hyperparameter combinations, a decision on which hyperparameter set to evaluate next is made. In our Bayes search, we used scikit-optimize to minimize expensive and noisy black-box functions.

LightGBM Analysis Details. The ML analysis was conducted using Python (v3.9.10.) and scikit learn 1.0.2. to detect factors which can predict individual spider fear. The chosen boosting method is gradient boosting decision tree, due to its accuracy, efficiency, and stability (Ke et al., 2017). All values were optimized. The maximum tree leaves for base learners were restricted between two and 2500. Base learners are trees, so the maximum number of leaves each decision tree consists of, has been set. The boosting learning rate determines the amount of contribution each model had on our prediction. Our rate was between 0.001 and 1. The number of boosted trees to fit is an important hyperparameter, comprising 100 to 2500 trees in our analysis. The trees were sequentially added to the model to correct and improve the predictions of prior trees. Between one and 250 datapoints was our minimum number of data needed in a leaf, also named child. The subsample ratio of columns when constructing each tree was between 0.001 and one. This is the fraction of randomly selected features used to train each tree. Further, the used L1 regularization term on weights lies between 0.001 and 1000, causing small values to turn zero.

Evaluating Model Performance

Statistical quality measures reporting our model results include MAE and R^2. In addition, SHAP values are reported, and a correlation matrix computed.

MAE. The MAE is the average of the absolute difference between the actual and predicted values of the data. The average of residuals in the data are measured and indicate how far a prediction was off on average. Smaller values indicate a better model fit. MAE values lie between 0 (perfect model fit, no error) and infinity (bad performing model). The values are not scale invariant; hence the values of the MAE depend on the scale of the target, in our case, fear. According to Willmott and Matsuura (2005), the MAE is the most natural measure of average error.

R^2. Also called the coefficient of determination, R^2 represents the proportion of the variance in the dependent variable that is explained by our regression model. The value of R^2 ranges from zero to one, whereas higher values indicate a better model fit. R^2 was used since it is a good and widespread metric to give a general idea of the performance of a model, in our case, a prediction. It shows for how much variance the model accounts for in a comprehensible manner and is suggested as a standard metric, having less interpretability limitations than other regression analysis evaluation metrics (Chicco et al., 2021).

Shapley Additive Explanations (SHAP). These values are used in model explanation and had the purpose of evaluating the contribution of every single feature in our model to the prediction. Positive SHAP values indicate positive impact on the prediction, while negative SHAP values indicate negative predictive impact (Lundberg & Lee, 2017).

Correlation Matrix. A correlation matrix of all input factors and the fear target was computed by using Pearson product moment correlation coefficients. It is useful in predicting the relationship between variables.

Results

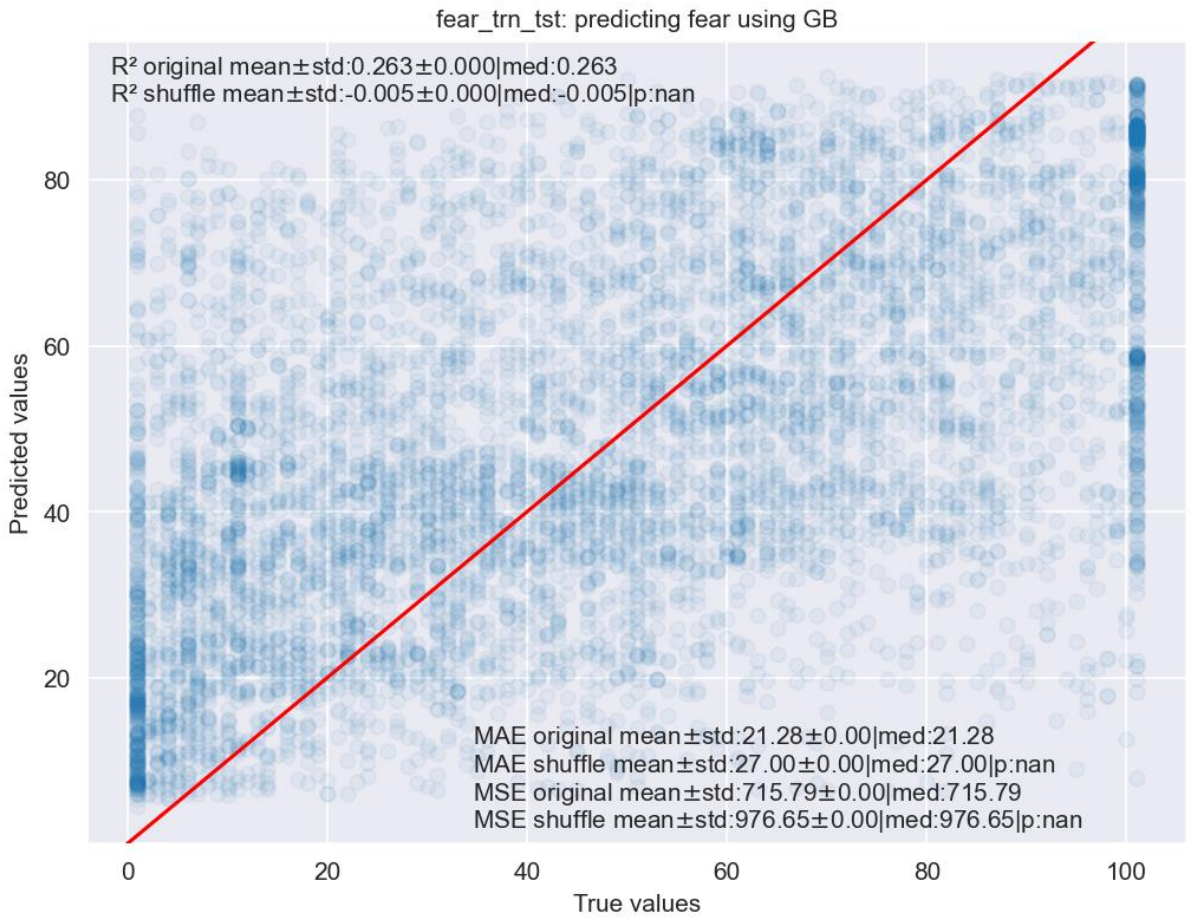
A LightGBM regression was computed to predict spider fear ratings for each individual of study 2, using questionnaire and demographic data of these individuals as predictors. As training data, spider image ratings and questionnaire data of study 1 participants were used. The model consisted of 12 input variables. Continuous predictors were fear mean, age, FSQ sum score, SPQ sum score, SAS sum score, STAI state sum score, STAI trait sum score, FEE sum score, SEE sum score, time sum, and DEG time. Gender was the single categorical predictor. Fear mean is the mean of the fear ratings of a holdout set of 50 study 1 individuals.

Model Performance

Our model was able to explain 26 percent of the variance, meaning that 26 percent of the variability observed in our target “fear” is explained by the regression model. The MAE of our regression is 21.28 points of fear ranking. Predictions can be made with ± 21 points precision on the fear rating scale from 1 to 101. With a chance prediction of 6 points, our model is better than a prediction by chance (Fig. 2).

Figure 2

Model Fit of the Fear Prediction Using All Features and Gradient Boosting, Plotting the Regressor Predicted Values Against the Given True Values.



Note. The model fit of our LightGBM regression is depicted, predicting our target (fear). The predicted fear values are plotted against the true fear values. 26 percent of the variability of our target could be explained by our model. The MAE, the average of the absolute difference between the actual and predicted values, is 21.28. Our prediction is 6 points better than by chance, and the precision of our prediction is ± 21 points within a fear rating range from 1 to 101.
fear_trn_tst = true fear values; GB = gradient boosting; R^2 = coefficient of determination; std = standard deviation; med = median; MAE = mean absolute error, MSE = mean squared error; p:nan = p value, not a number

Predictors

SHAP values were used to evaluate the contribution of every single predictive factor to the model's

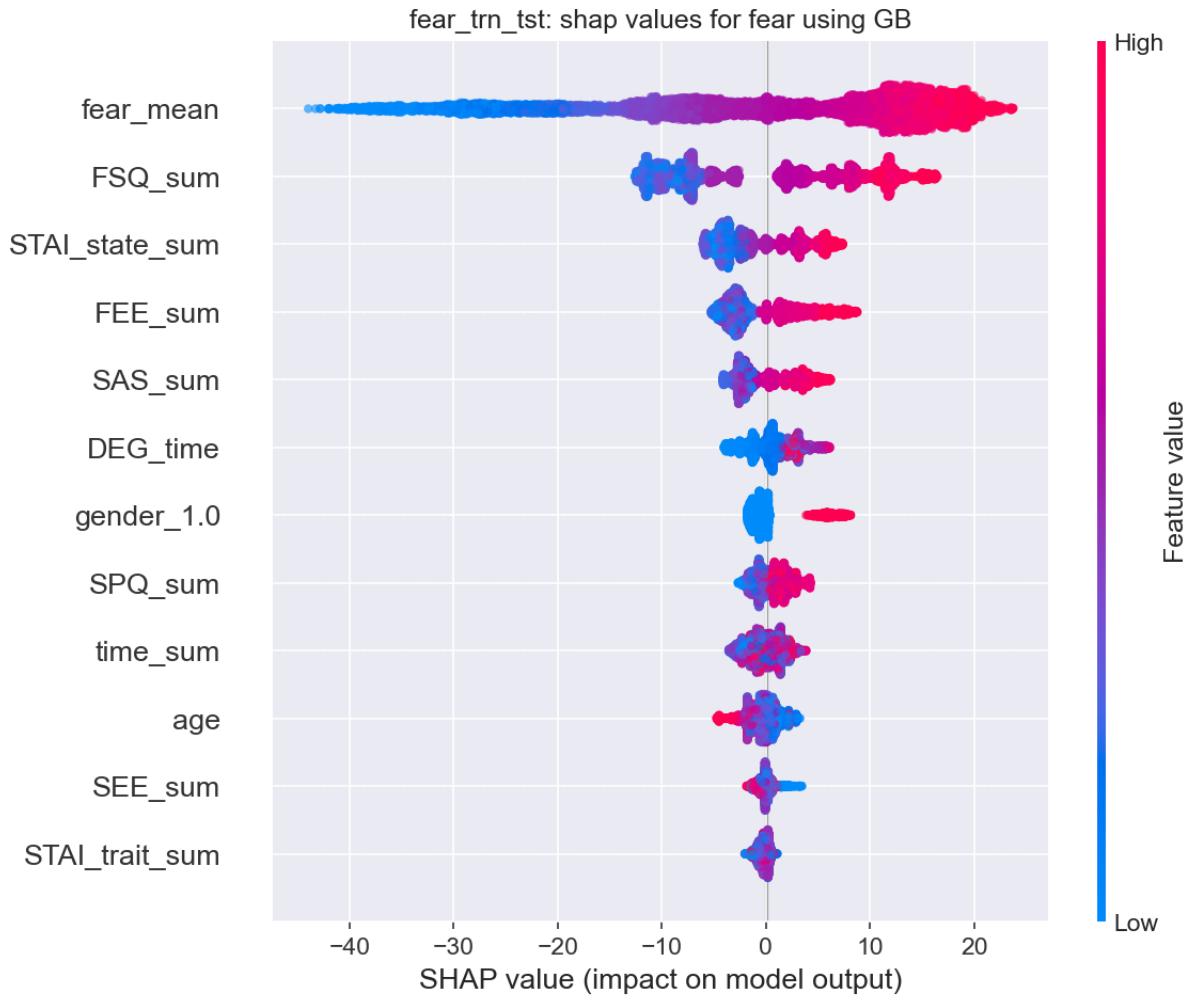
performance, the fear prediction (Fig. 3). These values show us the most important fear predictors which are, in descending order:

- Fear mean
- FSQ sum score
- STAI state sum score
- FEE sum score
- SAS sum score

The mean of all fear ratings of an image was the most important predictor in our analysis. The sum scores of the FSQ, STAI state, FEE, and SAS were also important predictors, while the predictive power decreased in descending order for the further factors: Deg time, gender, SPQ sum score, time sum, age, SEE sum score, and STAI trait sum score. However, a small but clear gender effect could be observed with gender_1.0, individuals identifying as women, being overall more fearful. Looking at this result, it is noteworthy to consider the unequal gender balance of this study: 26 participants identified as female, while only four participants identified as male, making it nearly impossible to generalize conclusions about male individuals and spider fear.

Figure 3

SHAP Values Depicting the Most Important Predictors for Our Model.



Note. The SHAP values illustrate the most important factors for predicting the target (fear) with our LightGBM regression model. Blue color indicates low feature values, while red color indicates high feature values. The most important predictors were fear mean, FSQ sum score, STAI state sum score, FEE sum score, and SAS sum score.

fear_trn_tst = true fear values; SHAP = shapley additive explanations; GB = gradient boosting

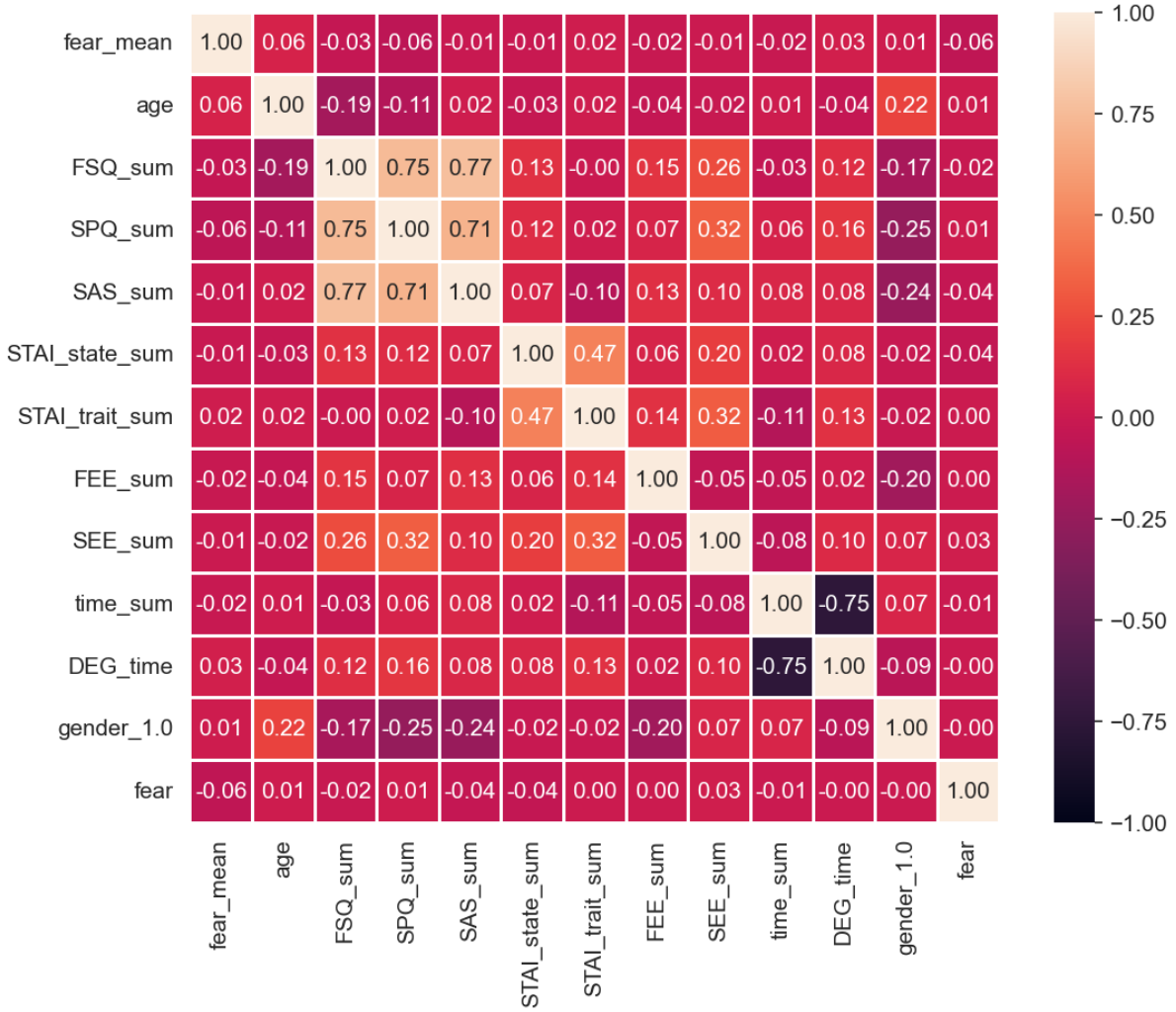
Correlations

A correlation matrix (Fig. 4) of all factors and the target fear was computed by using Pearson product moment correlation coefficients. There is no correlation with our target “fear”. All spider fear

questionnaires, SAS, SPQ, and FSQ are positively correlated with each other, indicating that they measure fear in a similar way. The variables time sum and deg time are negatively correlated with each other. This finding is not surprising, given that time sum is the total of minutes spent filling out the questionnaire, and deg time is a variable giving malus points for filling out the questionnaire extremely fast.

Figure 4

Full Correlation Matrix Illustrating the Association Between Predictive Features Among Themselves and Between Fear Target and Predictive Features of the Linear Regression Machine Learning Analysis.



Note. The three Spider Fear Questionnaires, Fear of Spiders Questionnaire (FSQ_sum), Spider Phobia Questionnaire (SPQ_sum), and Spinnenangst Screening (SAS_sum) are positively correlated with each other. DEG_time and time_sum correlate negatively with each other.

Taken together, the results of the ML analysis demonstrate a medium predictive effect, with fear mean, FSQ, STAI state, FEE, and SAS being the most important predictors for image elicited spider fear.

Discussion

The purpose of the present study was to identify whether a ML model with the input of questionnaire, demographic, and image rating data of spider-fearful individuals can predict subjective spider fear ratings on a scale from 1-101. Two comparable studies were conducted in which spider-fearful individuals viewed and rated images of spiders. Fear rating and questionnaire data of the first study was used to train our model. Questionnaire and demographic data of the second study, as well as a calculated fear mean per image of study 1 data were used as model predictors. The fear mean was calculated from data of 50 study 1 individuals, which were further part of the training data. A regression with a LightGBM algorithm was performed. This model was able to predict 26 percent of the variance of our target variable, which was fear. The results suggest that fear mean was the most important predictor. In addition, the sum scores of the FSQ, the STAI-state, FEE, and SAS were important predictors. Predictors contributing only marginally up to not at all in our model include DEG time, gender, SPQ sum, time sum, age, SEE sum, and STAI state sum.

To date, previous research has shown that ML approaches can be used to predict anxiety disorders (Pintelas et al., 2018), and treatment outcome (Hilbert et al., 2020; Forsell et al., 2020) efficiently. They have helped doctors to develop tools assisting them in predicting mental disorders, as well as supporting patient care. However, the accuracy of the results varies in consideration of the type of anxiety disorder, as well as the prediction methods (Pintelas et al., 2018). Our research was closely oriented to the work of Bălan et al. (2019, 2020) and Aue et al. (2021), having the same goal of predicting subjective fear levels in spider-fearful individuals, to soon be able to treat phobia with automatically estimated fear levels and adaptable exposure intensity. What is new about our approach is that two studies were used: One set for the spider fear prediction, and another individual and independent validation set to train the ML model. None of the related research discussed had implemented this before. Moreover, the main difference in this study is our approach of predicting fear on a continuous, rather than on a categorical scale. Expectedly, predicting fear on a continuous scale is a greater challenge and our model had less predictive power than the models of the related research did. As is observable in Bălan et al. (2019), the predictive power of their model already decreases from the two-level fear paradigm (fear/no fear) to the four-level paradigm (no fear/low fear/medium fear/high fear) by 4.63%. Another advantage of our study can be seen in the study of Aue et al. (2021) which observed the data of 27 participants; however, only 13 of the 27 individuals were afraid of spiders, while all our participants had spider fear. Additionally, our sample size is higher given the 30 participants to test our ML model, 151 to train the model, and 50 to calculate a fear mean. The study of Aue et al. (2021) further only included individuals identifying as female, while four of our participants identified as male.

Questionnaires and Demographics

Due to the results of our study, some questionnaires are suggested to have more predictive power than others. Concerning the SPQ, the study of Hellström and Ost (1996) could not identify the SPQ as a questionnaire with high predictive power. This can also be observed in our study. The SPQ was one of the questionnaires with least predictive power. Compared to the SPQ, it is suggested that the FSQ is superior in measuring non-phobic fear (Muris & Merckelbach, 1996). This as well is observed in our study, with the FSQ being the questionnaire with highest predictive power. Another study supporting the notion of the FSQ having high predictive power was conducted by Van Bockstaele and colleagues (2011). They found a positive correlation between the FSQ and avoidance behavior, as well as a positive correlation of the FSQ with skin conductance response increase, a popular physiological measure of fear. Interestingly, their data also indicates that the FSQ and STAI trait questionnaires were positively correlated with each other, even though the literature and our study suggest high predictive power for the FSQ, and low predictive power for the STAI trait.

According to Muris et al. (1998), the STAI trait questionnaire in general is a good predictor for behavior therapy outcome, showing that the higher the trait anxiety scores were, the less patients benefitted from therapy. Interestingly, the STAI trait sum scores were not a good predictor for subjective fear prediction in our study, while the STAI state sum scores were the second-best questionnaire predictor. Furthermore, the study by Eke & McNally (1996) found that STAI trait scores could not predict anxious responses to carbon dioxide challenge. Spielberger et al. (1970) also note that their STAI trait score predicts state anxiety in situations which elicit threat to self esteem, but not in situations with threat of pain or physical harm. This might explain low predictive value of STAI trait in studies as ours, yet not in the study of Van Bockstaele et al. (2011), since the threat to self esteem in their spider fear study probably did not differ strongly from that in our design. This leaves further room for investigation of the role of the STAI trait questionnaire. While research in fear prediction and STAI trait is broad, studies about fear prediction and STAI state seems to be rare. Further research is recommended since our study proposes a key role of the STAI state questionnaire in fear prediction.

Of the two disgust questionnaires, FEE and SEE in this study, the FEE was a significant predictor in our analysis. Although only one disgust predictor was important in our study, broad research on the role of disgust and disgust sensitivity in spider fear suggests that disgust is a crucial component (Leutgeb & Schienle, 2012a; Cisler et al., 2009; de Jong et al., 2002; Mulkens et al., 1996). Therefore, we recommend treating disgust as a potentially important predictor when researching the fear of spiders and including the FEE questionnaire. Aside from this, studies about the predictive power of German questionnaires, SAS, SEE, and FEE, is scarce and further research, especially for the

FEE, is recommended. For future fear of spiders research in general, to date we recommend including the spider fear questionnaires FSQ and SAS, the anxiety questionnaire STAI state, as well as the disgust questionnaire FEE.

Besides the questionnaires, we used the age of participants as a predictor. In the study of Walters (2001), age was a significant variable correlated negatively with STAI trait scores ($r(133)=-0.17$, $P<0.05$). This indicates that younger individuals had significantly higher anxiety scores than older individuals. This trend of fear ratings and age can also be observed in our study with younger aged participants expressing higher fear and older aged participants expressing lower fear. Yet, a preliminary conclusion cannot be drawn without evidence from further studies, especially since the age variance of our sample is very low.

Limitations and further directions

In this study, fear was predicted for only 30 participants. Of these 30 individuals, only four were male, which makes it nearly impossible to draw any specific conclusions about the male population. Moreover, a generalization to further anxiety disorders is not possible. A further limitation includes that due to a mistake only noticed after the analysis, one spider image was taken into the analysis twice. Therefore, there were only 313 different images. This needs to be addressed and changed in further analysis, yet, given the high number of images used, it is not to be expected that this changes the analysis results notably. At last, it is noteworthy that fear ratings of study 1 individuals may not have been the best predictor for fear ratings of individuals of study 2. The participants in study 2 viewed the images for the second time when rating them, since the first time viewing the images was in the MR. This might have caused loss of predictive power in the analysis. In addition, the two studies differed from each other in the fact that study two participants did a BAT before viewing the spider images in the passive viewing task. It may be possible that this has an impact on our results.

Future directions for this dataset include a second analysis with only significant features, to see if this leads to a more accurate fear prediction. Moreover, a further personalized analysis is suggested in which at first several data is gathered from every individual and subsequently the analysis is conducted. For example, to include the first ten ratings of an individual in the training data. In general, future research should examine the predictive impact of questionnaires and image ratings with larger sample sizes and with diverse phobic/anxiety disorders.

Furthermore, research in the area of VRET is recommended, since positive therapeutic effects have been shown (Botella et al., 2016; Lindner et al., 2020). Automated VRET could replace a therapist with gamification elements, which might play a crucial role in closing the treatment gap for anxiety disorders and phobias.

Conclusion

To conclude, our study identifies important variables for predicting subjective spider fear. Fear mean of images seem to be especially important for the prediction of fear in independent individuals. It is a first attempt at building a continuous scale of spider fear and an original approach using fear ratings of independent individuals for prediction. Automated and individualized ET has the potential to increase the number of affected individuals seeking help, to avoid an over- or underload of fear, reduce panic attacks, and therefore to reduce drop-out rates or recurrence for affected individuals already in therapy (Fernandez et al., 2015; Scholten et al., 2012). It would be made possible that individuals are only exposed to subjective threat-relevant stimuli, making ET more effective and efficient. Our study about subjective fear prediction examines and identifies new approaches and is a first step into the direction of making automated and individualized ET possible.

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