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„What attributes make spider images fearful or disgusting? Machine learning analysis investigating visual triggers contributing to aversion towards spiders"

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Abstract

Why are people afraid of spiders? Spider phobia is one of the most prevalent anxiety disorders in children as well as in adults. Yet we lack research investigating the basic characteristics of spiders that trigger sensations of fear as well as disgust. Thus, our aim was to identify the key attributes of spider images that trigger fear as compared to feelings of disgust. Results could reveal aspects of spider images with a high potential of leading to better treatment outcomes in individualized exposure therapy settings by using images of spiders with fear- or disgust-inducing attributes depending on the individual underlying visual triggers of the aversion towards spiders of the respective patient.

Our analysis consisted of the data from an online survey with *N*=152 spider-fearful participants rating fear and disgust levels of images of spiders and the categorization of those images. The data was then used to train our Machine Learning (ML) models for the targets "mean fear" and "mean disgust" utilizing Gradient-Boosted Decision Tree (GBDT) regression for the prediction of mean fear and disgust levels. Our ML models were able to explain 71.8% and 72.0% of the variance for the target variables "mean fear" and "mean disgust", respectively. Furthermore, our models were able to predict the targets "mean fear" and "mean disgust" with a Mean Absolute Error (MAE) of 7.20 and 7.50 points, compared to 16.41 and 16.64 points of a chance prediction, respectively. The analysis indicated that the size of the illustrated spider has a significant impact on perceived fear and disgust, whereas the presence of body hair of a spider was only predicting fear values significantly, but not values of disgust.

Concluding, our findings partially support evidence from previous studies, that the size of a spider as well as the visible presence of body hair are key attributes contributing to perceived fear and disgust towards spiders. Thus, our investigations contribute to laying the foundation for individualized exposure-based treatment concepts. Images of spiders with fear- or disgust-inducing attributes used in exposure therapy could be selected depending on the individual cause of the patients' aversion towards spiders leading to better outcomes.

Nevertheless, future research is needed to understand the underlying mechanisms and visual triggers of spider phobia, which is crucial for making exposure therapy more efficient.

Keywords: spider phobia, arachnophobia, exposure therapy, visual attributes of spiders, fear, disgust, machine learning analysis

Zusammenfassung

Warum haben Menschen Angst vor Spinnen? Spinnenphobie ist eine der am weitesten verbreiteten Angststörungen bei Kindern sowie bei Erwachsenen. Dennoch fehlt es an der Erforschung jener Charakteristika von Spinnen, die Gefühle der Angst und des Ekels auslösen. Aus diesem Grund war es unser Ziel, jene Attribute von Spinnen zu identifizieren, die Angst sowie Ekel auslösen, um herauszufinden, welche Aspekte von Abbildungen von Spinnen ein höheres Potenzial für bessere Therapieerfolge besitzen. Anhand dieser Erkenntnisse wäre es möglich, personalisierte Therapiekonzepte zu entwickeln, indem Bilder von Spinnen verwendet werden, die eher mit Angst oder Ekel assoziiert sind, je nachdem welches der beiden Gefühle der individuelle Auslöser für die Abneigung gegen Spinnen bei dem/der PatientIn ist.

Unsere Analyse bestand aus den Daten einer online Umfrage mit N=152 Teilnehmern mit Angst vor Spinnen, die Abbildungen von Spinnen hinsichtlich Angst sowie Ekel bewerteten, und der Kategorisierung jener Abbildungen. Die Daten wurden dann verwendet, um die beiden *Machine Learning (ML)* Modelle mithilfe einer *Gradient-Boosted Decision Tree (GBDT) Regression* für die Zielvariablen „Angst“ und „Ekel“ zu trainieren, um jene dann vorhersagen zu können. Die ML Modelle waren in der Lage, 71.8% bzw. 72.0% der Varianz für die Zielvariablen „mittlere Angst“ bzw. „mittlerer Ekel“ zu erklären. Weiters waren die Modelle in der Lage, die Zielvariablen „mittlere Angst“ bzw. „mittlerer Ekel“ mit einer Präzision von 7.20 bzw. 7.50 Punkten vorherzusagen, im Vergleich zu 16.41 bzw. 16.64 Punkten einer Zufallsvorhersage. Die Analyse zeigte einen signifikanten Einfluss der Größe der Spinne auf Angst sowie Ekel, wohingegen das Vorhandensein von Körperbehaarung der Spinne nur Angst, aber nicht Ekel, signifikant vorhersagen konnte.

Unsere Ergebnisse stimmen zum Teil mit vorangegangenen Studien überein, die ebenfalls zeigten, dass die Größe sowie Behaarung einer Spinne zentrale Attribute darstellen, die Angst sowie Ekel bei Personen mit Spinnenphobie auslösen. Unsere Ergebnisse tragen zur Bildung der Grundlage für automatisierte und individualisierte Konfrontationstherapie bei. Dennoch ist zukünftige Forschung essenziell, um die Mechanismen, die Spinnenphobie zugrunde liegen, verstehen und Therapieansätze effizienter gestalten zu können.

Schlagwörter: Spinnenphobie, Arachnophobie, Konfrontationstherapie, visuelle Attribute von Spinnen, Angst, Ekel, machine learning analysis

Contents

Introduction

Spider Phobia: Epidemiology & Pathology

Phobias are one of the most known and widespread psychopathologies (Fendt & Fanselow, 1999). Research indicates a lifetime prevalence of any specific phobia of about 3.4% to 12.5%, depending on the country or region (Iancu et al., 2007; Kessler et al., 2005; Park et al., 2013; Zsido et al., 2018). With 3.3% to 5.7%, zoophobia has the highest lifetime prevalence of the five subtypes of specific phobia: zoophobia (fear triggered by animals or insects), natural environment phobias (fear triggered by heights, storms or darkness), situational phobias (fear triggered by bridges, flying, driving or tunnels), blood-injection-phobias (fear triggered by seeing blood, receiving an injection or injury) and other phobias, like for example fear of loud noises (American Psychiatric Association, 2013; LeBeau et al., 2010). Furthermore, zoophobias generally are about four times more prevalent in female than in male individuals (Frederikson et al., 1996).

Spider phobia, or arachnophobia, from the Greek words 'arachne' for spider and 'phobos' for fear, is one of the most prevalent anxiety disorders in children as well as in adult individuals, and is characterized by persistent, irrational fear triggered by anticipated or actual presence of one or more spiders (Ollendick, 1983; Schienle et al., 2005; Polák et al., 2020). Due to the relatively high prevalence of about 2.7% to 9.5% in the general population, depending on the country and environment, spider phobia is of great interest for researchers investigating the underlying mechanisms as well as clinical treatment options and prevention initiatives (Frederikson et al., 1996; Oosterink et al., 2009; Zsido, 2017; Zsido et al., 2018).

According to the Diagnostic and Statistical Manual of Mental Illnesses (DSM-V; American Psychiatric Association, 2013), specific phobia is characterized by exaggerated, persisting fear of a specific object or situation, which almost always triggers immediate fear and is actively avoided by the individual suffering from the phobia resulting in distress and impairment of functioning in several important areas for six months or more. People suffering from severe spider phobia may even be too afraid to go into their garage or basement because a spider could be there limiting and impairing their daily life. Spider phobia is also associated with increased risk for other comorbid anxiety disorders and several psychological disorders, including depression (Beesdo-Baum et al., 2009; Leehr et al., 2021; Wardenaar et al., 2017).

The Spider Questionnaire (SPQ; Watts & Sharrock, 1984) and the Fear of Spiders Questionnaire (FSQ; Szymanski & O'Donohue, 1995) are the tools most frequently utilized to diagnose spider phobia in adults. Treatment approaches include in vivo exposure, systematic desensitization, imaginal exposure, virtual reality (VR) or computer assisted exposure, cognitive behavioral therapy (CBT) and progressive muscle relaxation (Wolitzky-Taylor et al., 2008). About 60-85% of individuals suffering from specific phobias never seek treatment (Boyd et al., 1990; Magee et al., 1996). Therefore, it is of great importance to investigate and create novel treatment strategies within a more accessible format to increase the motivation of individuals to seek help.

Exposure Therapy in Spider-phobic Individuals

Exposure therapy currently is considered as the gold standard for treating specific phobia and is based on fear extinction principles (Davis et al., 2006; Leuchter et al., 2022). The controlled exposure to the feared stimulus reduces anxiety while limiting the opportunity of avoidance or escape from the stimulus itself (Benito & Walther, 2015). For successful reduction of the fear, the individual has to learn that the fearful stimulus is generally safe, that triggered emotions are safe, temporary, and manageable and that safety behaviors are not necessary, which is acquired by "repeated and prolonged direct experience approaching or interacting with the feared animal in different contexts" (Abramowitz, Deacon, & Whiteside, 2019, pp. 138).

Exposures can be based on the two dimensions proximity or salience, or a combination of the manipulation of both variables, depending on the individual characteristics of the patient (Abramowitz et al., 2019). Exposure based on proximity involves reducing the distance between the feared stimulus and the patient in manageable steps, like for example reducing the distance between a real spider and the patient step by step, while exposure based on salience concentrates on confrontation to exposure lists, like for example exposure to images of spiders followed by videos and then progressing to real spiders (Abramowitz et al., 2019). The choice of the exposure approach can differ across patients and is dependent on the individual fear or anxiety characteristics of the patient (Abramowitz et al., 2019). Research indicates strong effects of in vivo exposure therapy on self-reported ratings as well as on behavioral avoidance and is generally recommended as first-line treatment (Andersson et al., 2009; Wechsler et al., 2019; Zlomke & Davis, 2008).

During the last years, VR exposure therapy has become of great interest for treatment of several psychological disorders, especially anxiety disorders like spider phobia (Carl et al., 2019). Benefits of VR exposure therapy include that the patient does not need to directly interact with the feared stimulus, which generally increases the motivation to seek treatment, and it is also not necessary to collect and store live animals for the sake of therapy of anxiety disorders (Garcia-Palacios et al., 2007; Reuterskiöld & Öst, 2012). VR exposure therapy generally has shown high efficacy in several randomized-controlled trials (Hoffman et al., 2003; Leehr et al., 2021; Michaliszyn et al., 2010; Minns et al., 2018). A controlled trial conducted by Garcia-Palacios et al. (2002) showed a clinically significant improvement of 83% in patients receiving VR exposure therapy as compared to 0% in the control group. Miloff et al. (2019) compared in vivo one-session exposure therapy with VR exposure therapy and found strongly reduced avoidance behavior and self-reported fear for both therapies. Additionally, a recent study showed similar effects of in vivo and VR exposure therapy regarding electroencephalography (EEG) measures indicating equal reduction of affective responses to spiders on a physiological level for the two different treatment approaches (Wiens et al., 2022).

Fear vs. Disgust in Spider Phobia

Am I only disgusted or am I experiencing actual fear? Both fear and disgust have been objects of research when it comes to the underlying mechanisms and reasons for phobias in general and have both been found to be contributing to several phobias (Abramowitz et al., 2019; Cisler et al., 2009; Davey, 2011; Matchett & Davey, 1991).

The sensation of *fear* is one of the most overwhelming emotions a human being can experience and can be considered as an activation of the *Defensive Behavioral System* that serves as a protection against potentially dangerous objects, situations, or threats (Fanselow, 1991; Fendt & Fanselow, 1999). Physiologically, fear is characterized by an accelerated heart rate and a distinct facial expression, including widely opened eyes and drawn back corners of the mouth (Izard, 1977; Lipp, 2006). On the behavioral level, fear is associated with avoidance of feared objects, animals (like spiders), or situations, wanting to escape, or, on the other hand, becoming immobile, tensing-up, and freezing as well as asking other individuals to remove the feared object in case avoidance of the situation is not possible (Abramowitz et al., 2019; Izard, 1977).

However, fear is not necessarily dependent on the actual presence of danger but rather is a result of the misappraisal of the likelihood of danger (Abramowitz et al., 2019). For instance, spider-fearful individuals have shown to overestimate the size and the approaching speed of spiders (Vagnoni et al., 2012; Vasey et al., 2012).

The feeling of *disgust* is considered to be universal, triggering a distinctive facial expression, including drooping of the corners of the mouth, feelings of nausea, fear of contamination as well as avoidance of certain disgusting objects (Ekman et al., 1983; Rozin & Fallon, 1987; Stark et al., 2005; Woody & Teachman, 2000;). Disgust has been found to be directly related to the degree of animal phobias in general, but especially to small animals that are generally not likely to attack or harm human beings but are considered fearful, such as spiders or cockroaches (Davey, 2011; Matchett & Davey, 1991). Even if people are rationally acknowledging that a certain animal is unlikely to harm them, they can still experience an overwhelming aversion towards the animal simply thinking about, for example, a spider crawling over their hand (Abramowitz et al., 2019). For those cases, disgust may be more prone than fear itself, but disgust could be misinterpreted as fear by the individual (Abramowitz et al., 2019).

Research indicates that disgust could be an evolutionary result of certain animals to be associated with the spreading of diseases, contamination, and dirt, rather than them being truly harmful or attempting to attack human beings (Davey, 2011; Izard, 1977; Marzillier & Davey, 2004; Matchett & Davey, 1991). Rozin and Fallon (1987) have pointed out that nearly all objects triggering feelings of disgust are animals, related to animals or were in close contact to animals. This would suggest disgust being a food-related, disease-avoidance emotion evoking an underlying sensitivity to contamination (Davey, 2011; Marzillier & Davey, 2004; Matchett & Davey, 1991). It is unclear, how exactly spiders have become a target of disease-avoidance responses, however Davey (1994) mentions that there could be an association between the development of the fear of spiders and the vast epidemics that European cultures suffered from since the Middle Ages that may have evoked an association between spiders and diseases.

Concluding, both fear and disgust result from misassumptions regarding the consequences of a potential confrontation with a feared animal (Abramowitz et al., 2019; Vagnoni et al., 2012; Vasey et al., 2012). Research shows that spiders can be associated with fear as well as with disgust (Abramowitz et al., 2019; Cisler et al., 2009; Davey, 2011; Matchett & Davey, 1991). De Jong and Muris (2002) have found evidence supporting "the idea that spider phobia essentially reflects a fear of physical contact with a disgusting stimulus" (pp. 51). Furthermore, research has shown a reduction of symptoms after exposure therapy associated with the reduction of disgust (Olatunji et al., 2011). Concluding, fear and disgust both contribute to spider phobia and seem to be confounded resulting in a continuing debate regarding the reason why spider phobic individuals truly are distressed by these animals (Huijding & de Jong, 2007; Woody & Teachman, 2000).

Attributes of Spiders Evoking Fear and Disgust

According to the *habituation model*, the activation of fear is crucial for the effectiveness of the exposure to the feared stimulus (Foa & Kozak, 1986). The study of Davey (1991) showed that "legginess" may be the most frightening attribute of spiders, closely followed by movement-related features. Similarly, the study of Lindner et al. (2019) revealed that movement-related aspects and appearance of the spider, including size and "legginess", were of importance and were rated highest by spider-fearful individuals, pointing out the importance of movement patterns as used in VR exposure therapy. Additionally, Zvariková et al. (2021) showed that enlarged chelicerae and abdomen as well as the presence of body hair triggered higher levels of perceived fear and disgust; longer legs also triggered fear within this study.

Investigating the characteristics of spiders that trigger fearful reactions is crucial both for VR as well as for in-vivo exposure therapy. Therefore, we used the data from an online survey that was conducted within a previous experiment of our research team to investigate the levels of fear and disgust triggered by images from the Spider Images Database (SpiDa), to assess mean ratings of "fear" and "disgust" for each image that is part of the database. In the next step, all 313 images of the database were categorized by five members of our research team regarding the attributes illustrated in Table 1. The gathered data was then used to calculate regression models using Gradient-Boosted Decision Tree (GBDT) to predict “mean fear” and “mean disgust” ratings per image from the data of *N*=152 spider-fearful participants, who rated the images in a previous study.

Aim and Purpose

With our data we aim to identify the key attributes of spider images that trigger fear as opposed to feelings of disgust. Results could reveal aspects of spider images with a high potential of leading to better outcomes of exposure therapy. Additionally, findings could provide future directions for the creation of novel treatment strategies within a more accessible format to increase the motivation of people suffering from spider phobia to seek help (Boyd et al., 1990; Magee et al., 1996). Considering the lack of research investigating fear- and disgust-inducing cues triggering aversion towards spiders, it is an interesting and very important topic to investigate.

Hypothesis

Our intention is to predict “mean fear” and “mean disgust” on a rating scale between zero and 100 (Shea, 2022).

Methods

SpiDa: The Spider Images Database

The Spider Images Database (SpiDa) is a database which consists of 313 images of spiders (800x600px each) including images of spiders of various sizes (small, middle, large), species and textures (hairy, smooth). The number of spiders depicted in one image varies as well as the distance to the camera (close, distant) and the environment (civilization, nature, human contact). Some images include cobwebs as well and some show spiders eating other animals. The spider images were sourced from free stock photos and the Geneva Affective Picture Database (GAPED) among others, and some images were self-taken (Dan-Glauser & Scherer, 2011).

Figure 1

Examples of spider images of the database

Note. Different spider images that are part of the database and were used in the online survey.

Categorization of Spider Images

All images were assessed by five non-spider-fearful members of the research team, aged between 22 and 31 years (*M* = 26.6, *SD* = 3.4) regarding the categories illustrated in Table 1. Selection of the categories was based on previous research of Zvaríková et al. (2021) indicating size, texture, and visibility of the legs of the spider being the attributes triggering the most fear and disgust, as well as on a previous thesis of a member of the research team investigating the database using a similar set of categories (Eder, 2020). The categorization was then used to analyze the contribution of each feature, like for example visibility of the eyes of the spider, subjective size of the spider or number of spiders shown in the image.

The variable "not evaluable" was introduced for most of the categories to be able to exclude images from a specific analysis that cannot be allocated to one of the attributes to further prevent or minimize distortion of the analysis.

To be able to categorize each image unambiguously, an uneven number of members of the lab assessed the images; at least three lab members had to independently choose the same attribute for a category to allocate an image to an attribute. Frequencies of categorization ratings are illustrated in Table 2 and Figure 2.

On average, 70.4% (*SD* = 21.2, *range* = 36.7-96.2) of the images were allocated to the same attribute within a category by all five study team members, 16.5% (*SD* = 10.1, *range* = 3.5-29.0) of the images were allocated to the same attribute by four study team members and 13.1% (*SD* = 11.7, *range* = 0.3-36.7) of the images were allocated to the same attribute by three study team members.

Table 1

Frequencies of different attributes of spider images of the Spider Images Database (SpiDa)

Category	*Attribute*	*Number of images (N, %)*
Spider in picture	no spider	30 (9.6)
	spider	260 (83.1)
	artificial/painted/comic spider	23 (7.3)
Cobweb in picture	no	197 (62.9)
	yes	116 (37.1)
Number of spiders	none	29 (9.3)
	1 spider	259 (82.7)
	2 or more spiders	25 (8.0)
Subjective distance to spider	not evaluable	36 (11.5)
	close	252 (80.5)
	distant	25 (8.0)
Environment	not evaluable	61 (19.5)
	nature	152 (48.6)
	civilization	43 (13.7)
	human contact	57 (18.2)
Texture of spider	not evaluable	51 (16.3)
	smooth	136 (43.4)
	hairy	126 (40.3)
Eyes of spider	not evaluable	30 (9.6)
	non-visible	182 (58.1)
	visible	101 (32.3)
Eating prey	not evaluable	30 (9.6)
	not eating prey	260 (83.1)
	eating prey	23 (7.3)
Subjective size of spider	not evaluable	31 (9.9)
	small	62 (19.8)
	middle	115 (36.8)
	large	105 (33.5)
Perspective	not evaluable	43 (13.7)
	from side/front	165 (52.7)
	from top/bottom	105 (33.6)
Colour of picture	black/white	7 (2.2)
	colour	306 (97.8)

Note. The categorization of the 313 images is based on the subjective assessment of five members of the lab.

Table 2

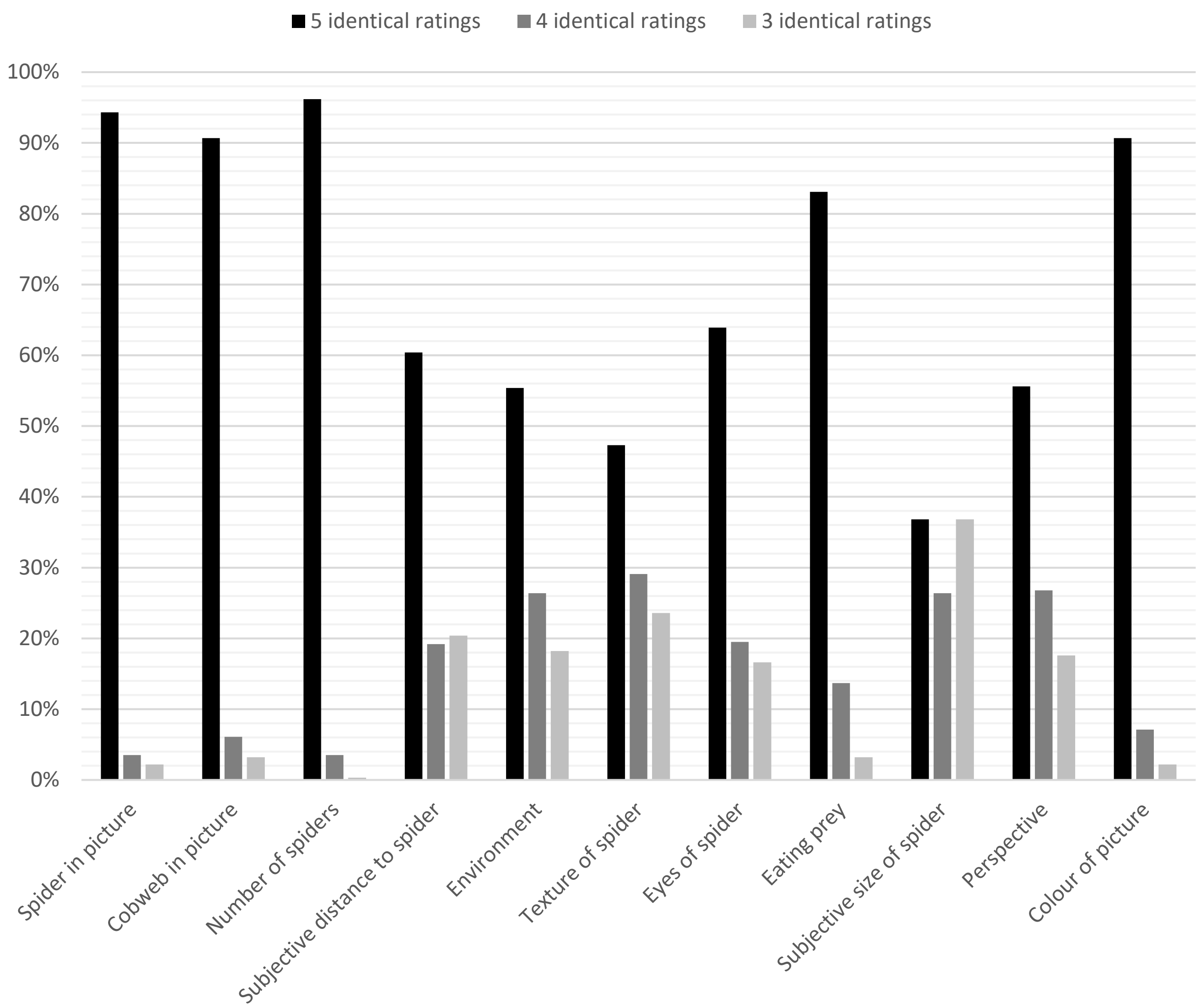
Frequencies of identical categorization ratings

Category	*Number of identical ratings*	*Number of images (N, %)*
Spider in picture	5	295 (94.3)
	4	11 (3.5)
	3	7 (2.2)
Cobweb in picture	5	284 (90.7)
	4	19 (6.1)
	3	10 (3.2)
Number of spiders	5	301 (96.2)
	4	11 (3.5)
	3	1 (0.3)
Subjective distance to spider	5	189 (60.4)
	4	60 (19.2)
	3	64 (20.4)
Environment	5	173 (55.4)
	4	83 (26.4)
	3	57 (18.2)
Texture of spider	5	148 (47.3)
	4	91 (29.1)
	3	74 (23.6)
Eyes of spider	5	200 (63.9)
	4	61 (19.5)
	3	52 (16.6)
Eating prey	5	260 (83.1)
	4	43 (13.7)
	3	10 (3.2)
Subjective size of spider	5	115 (36.8)
	4	83 (26.4)
	3	115 (36.8)
Perspective	5	174 (55.6)
	4	84 (26.8)
	3	55 (17.6)
Colour of picture	5	284 (90.7)
	4	22 (7.1)
	3	7 (2.2)

Note. Illustration of the frequency of five, four or three identical ratings calculated per image and summarized per category based on the subjective categorization of five members of the lab.

Figure 2

Illustration of the frequencies of identical categorization ratings



Note. Illustration of the frequency of five, four or three identical ratings calculated per image and summarized per category based on the subjective categorization of five members of the research team.

Online Survey & Participants

To investigate the attributes of spiders that evoke fear as well as disgust, an online trial via *SoSci Survey* was conducted within a previous experiment of the research team using SpiDa and several questionnaires.

At the beginning of the survey, the participants were presented with the *Fear of Spiders Questionnaire* (FSQ; Szymanski & O'Donohue, 1995), followed by the *Spider Phobia Questionnaire* (SPQ ;Watts & Sharrock, 1984) and the *State-Trait Anxiety Inventory* (STAI; Spielberger, 1983) in the validated German versions, as well as the "Skala zur Erfassung der Ekelsensitivität" [Scale for Assessing Disgust Sensitivity] (SEE; Schienle et al., 2010) and the "Fragebogen zur Erfassung der Ekelempfindlichkeit" [Questionnaire for the Assessment of Disgust Responsiveness] (FEE; Schienle et al., 2002) in the original German versions.

After answering the questionnaires, the participants were presented with the spider images. Each image was displayed for three seconds followed by a twelve second time window for the rating of the image regarding the three dimensions "fear", "disgust" and "willingness to approach". The attribute *fear* was represented by the question "Wie viel Angst löst dieses Bild in Ihnen aus?" [How much fear does this picture elicit in you?] on a scale between zero and 100. The attribute *disgust* was represented by the question "Wie viel Ekel löst dieses Bild in Ihnen aus?" [How much disgust does this picture elicit in you?] on a scale between zero and 100. The last attribute *willingness to approach* was represented by the question "Wie nahe könnten Sie in den abgebildeten Inhalt herankommen, wenn Sie Ihre Angst überwinden wollen?" [How close could you get to the content shown in the picture, if you wanted to overcome your fear?] on a scale between zero meters, indicating physical touch, and ten meters, respectively. Schematics of the image-ratings are displayed in Figure 3.

Each participant was presented with 95 images randomly selected out of the 313 images of the database with 20% of these images having the possibility to be presented twice to the participant, to test whether ratings would change due to habituation, three catch-trials to correct the possibility of guesswork by showing a short instruction instead of an image, instructing the participant what to move the cursor either to the very left or the very right side of the scale, and two neutral images in-between.

In the last phase of the trial, participants were presented with the FSQ again, and another time for the follow-up one week after the completion of the survey.

Figure 3

Schematics of an image-rating trial

Note. Illustration of the rating of an image regarding fear, disgust, and willingness to approach.

The online survey was published at *Laboratory Administration for Behavioral Sciences* (LABS) of the Faculty of Psychology. The sample consisted of individuals with self-reported fear of spiders and the median processing time of the survey was approximately 38 minutes. Informed consent was obtained before start of the experiment.

In total, *N*=193 spider-fearful individuals completed the survey. After excluding all individuals with a pre-study FSQ below 24, *N*=152 participants (81.6% female, 17.8% male, 0.6% diverse) aged between 18 and 45 (*M* = 23.0, *SD* = 4.0) represented the final sample.

Within this thesis, only the image-specific mean ratings of fear and disgust were used, since the primary scope of this thesis is the categorization of the images and the analysis of the respective data. The detailed experimental paradigm results of the online survey will be reported elsewhere.

Machine Learning (ML) Analysis

Machine Learning (ML) is a highly interdisciplinary branch of research based on concepts from various disciplines of science, including optimization theory, artificial intelligence, statistics, cognitive science and information theory, among others, and is serving a broad range of possible applications (Imanbayev et al., 2022; Zaslavsky, Perera & Georgakopoulos, 2013).

Two different ML models were carried out. In the first analysis, the prediction target was the “mean fear” rating per image. In the second analysis, the prediction target was the “mean disgust” rating per image. Gradient-boosted decision tree (GBDT) regression was used as the predictive algorithm between the prediction targets (Y), illustrated in Table 3, and the predictors (X), illustrated in Table 4. Nested cross-validation was used to carry out hyperparameter tuning in the inner cross-validation loop to improve predictive performance of the models by avoiding overfitting. Modified t-tests were used to calculate statistical significance of the importance of the predictors (Nadeau & Bengio, 2003). Bonferroni correction was applied if needed to correct for multiple comparisons (Giordano et al., 2022; Nadeau & Bengio, 2003).

Table 3

Targets and definitions used for the ML analysis

Target	*Definition*
fear_mean	fear mean of the image ratings
disgust_mean	disgust mean of the image ratings

Note. The illustrated targets were used as prediction (Y) for GBDT regression ML analyses.

Our ML analysis was conducted using Python (v3.10.6) and scikit-learn (v1.1). The number of tree leaves for base learners for the GBDT regression was searched between 2 and 100 leaves. The number of datapoints needed per leaf, also named child, was searched between 1 and 100. The number of boosted trees to fit our model was searched between 100 and 1000 trees. The boosting learning rate was searched between 0.001 and 1. Furthermore, L1 regularization was searched between 0.001 and 1000.

Table 4

Predictors and definitions used for the ML analysis

Predictor	*Definition*
spider_in_picture_0.0	no spider in picture
spider_in_picture_1.0	spider in picture
spider_in_picture_2.0	artificial/painted/comic spider in picture
number_of_spiders_0.0	no spider in picture
number_of_spiders_1.0	one spider in picture
number_of_spiders_2.0	two or more spiders in picture
texture_of_spider_0.0	texture of spider not evaluable
texture_of_spider_1.0	smooth texture
texture_of_spider_2.0	hairy texture
eyes_of_spider_0.0	visibility of eyes of spider not evaluable
eyes_of_spider_1.0	eyes of spider not visible
eyes_of_spider_2.0	eyes of spider visible
subjective_size_0.0	subjective size of spider not evaluable
subjective_size_1.0	subjective size of spider is small
subjective_size_2.0	subjective size of spider is middle
subjective_size_3.0	subjective size of spider is large
subjective_distance_of_spider_0.0	subjective distance of spider is not evaluable
subjective_distance_of_spider_1.0	subjective distance of spider is close
subjective_distance_of_spider_2.0	subjective distance of spider is distant
color_of_picture_1.0	picture is in color
eating_prey_0.0	spider is eating prey is not evaluable
eating_prey_1.0	spider is not eating prey
eating_prey_2.0	spider is eating prey
environment_0.0	environment is not evaluable
environment_1.0	environment is nature
environment_2.0	environment is civilization
environment_3.0	environment is human contact
cobweb_in_picture_1.0	cobweb in picture
perspective_0.0	perspective of spider is not evaluable
perspective_1.0	perspective of spider is from side/front
perspective_2.0	perspective of spider is from top/bottom

Note. The illustrated predictors were used as input (X) for linear regression ML analysis. Definitions of the predictors were determined prior to categorization of the images.

Gradient-Boosted Decision Tree (GBDT) Regression

GBDT was used for our analyses which is a supervised ML algorithm for regression problems. The idea of GBDT is to use multiple weak models (weak learners) sequentially to minimize the overall prediction errors of the additive model (Ke et al., 2017; Natekin & Knoll, 2013).

The following input is required for GBDT:

- **A Loss Function (L).** Models are fit by using an arbitrary differentiable loss function. The loss function defines how the algorithm models the data set and is the difference between actual and predicted values (Natekin & Knoll, 2013). For our models, we used the Mean Absolute Errors (MAE) or L1 Regression Loss.
- **Weak Learners.** Weak learners are the models that are used to reduce the prediction error generated from the previous model to produce a strong model at the end. Weak learners consist of decision trees that produce an accuracy that is only slightly superior to random guessing (Natekin & Knoll, 2013).
- **An Additive Model.** In GBDT, the decision trees are added sequentially, and existing trees are not changed within the model. Each added tree will correct the prediction error made by prior models. A gradient descent technique minimizes losses when adding trees resulting in its name “gradient boosting”, since the model is fit as the loss gradient is minimized (Natekin & Knoll, 2013).

Advantages of GBDT include the predictive accuracy, which is generally high, and the flexibility, which allows an optimization on different loss functions and provides several different hyperparameter tuning options. Additionally, data pre-processing is usually not required, and GBDT algorithms can be used for categorical as well as numerical data sets. However, GBDT tend to overfit training data, therefore, hyperparameter tuning within an inner (nested) cross-validation loop is mandatory to obtain good predictions as described in the following sections. GBDT often require many decision trees, leading to computational expensiveness since analyses can be very time and memory exhaustive (Ke et al., 2017; Natekin & Knoll, 2013).

Hyperparameter Tuning with Bayesian Optimization

In ML analyses, *hyperparameters* determine how the model is structured and as opposed to the model parameters, hyperparameters cannot be estimated by the model from the present data (Bischl et al., 2021).

Hyperparameter tuning, or hyperparameter optimization, is the process of determining the optimal combination of hyperparameters that maximize the performance of the final model. Hyperparameter optimization will identify the combination of hyperparameters that is best suited for the model and will control model complexity as well as avoid overfitting (Bischl et al., 2021; Weerts, Mueller & Vanschoren, 2020). Since ML algorithms are highly adjustable by their hyperparameters, those must be selected cautiously to achieve optimal results (Bischl et al., 2021). Therefore, appropriate algorithms are used for the mathematical formalization of hyperparameter optimization to increase efficiency and ensure reproducibility (Bischl et al., 2021).

We used *Bayesian Optimization* for our analyses, which is a global optimization method for expensive black-box functions (Bischl et al., 2021). Bayesian Optimization is an iterative algorithm that uses the probability to find the minimum of a function to find the input value to a function which produces the lowest possible output value (Wang et al., 2020; Bischl et al., 2021). Furthermore, we used scikit-optimize (v0.9), a sequential model-based optimization algorithm to receive optimal solutions for hyperparameter search problems.

Nested Cross-Validation

Nested Cross-Validation is a popular resampling procedure to model hyperparameter optimization and model selection that attempts to overcome the problem of overfitting the training dataset, by estimating the generalization error of the underlying model and its hyperparameter and parameter search (Berrar, 2018; Cawley & Talbot, 2010; Hastie, Tibshirani & Friedman, 2009).

Nested Cross-Validation consists of a double loop: The inner loop is represented by the parameters set used to optimize the training criterion and exhibits the selection of the model and parameters, while the outer loop is represented by the hyperparameters used to optimize the model selection criterion and assesses the quality of the model (Cawley & Talbot, 2010). Hence, Nested Cross-Validation is also known as “Double Cross-Validation” (Stone, 1974).

Model selection done without Nested Cross-Validation uses the same data to adjust the model parameters and to evaluate the model performance, which potentially could result in overfitting of the data; however, the magnitude of the effect is mainly subordinate to the size of the dataset as well as to the stability of the model (Cawley & Talbot, 2010).

Nested Cross-Validation was used for our analyses for selecting the optimal set of hyperparameters, hyperparameter search and for estimating the model error, as well as to prevent overfitting and data leakage (Berrar, 2018; Hastie et al., 2009). The number of splits for our inner loop was set to a minimum of 10 and a maximum of 200. Number of cross-validation repetitions for our outer loop was 100, while the number of predictions of our inner loop was 10000. The models were trained using 80% of the mean image-ratings of “fear” and “disgust” of the total N=152 participants and the categorization as shown in Table 1 to predict the remaining 20% of the data.

Shapely Additive Explanations (SHAP)

Shapley Additive Explanations (SHAP) values are used to measure feature importance and to evaluate the contribution of every single predictor in the model to the target (Lundberg & Lee, 2017). SHAP values do not only show a potential feature importance, but also indicate whether the feature has a positive or a negative impact on the target: Positive SHAP values indicate positive predictive impact of the predictors, and negative SHAP values indicate negative predictive impact (Lundberg & Lee, 2017). Using SHAP values, it is possible to assess how each feature contributes to a single target (Lundberg & Lee, 2017). For our analysis, we calculated the contribution of each predictor, as illustrated in Table 4, to each target, as illustrated in Table 3.

Evaluating Model Performance

For our ML models, the following statistical quality measures were used:

R^2. The coefficient of determination, R-squared or R^2, is used to quantify the extent to which the dependent variable is determined by the independent variables, also known as proportion of variance. R^2 values range from zero to one, indicating trivial fit with a horizontal fitted line and perfect fit, respectively. Negative infinite values are also possible and indicate a worse than trivial fit (Chicco et al., 2021).

MAE. The Mean Absolute Error (MAE) describes average model-performance by summing the individual model-prediction errors to calculate the ‘total error’ and then dividing it by n, producing MAE values between zero and infinity, indicating perfect model fit with no error and a bad performing model, respectively (Chicco et al., 2021; Willmott & Matsuura, 2005).

Results

The Gradient-Boosted ML algorithm for regression was used to predict “mean fear” as well as “mean disgust” ratings in two different analyses using the predictors illustrated in Table 4. Overall, the model consisted of 28 binary (yes vs. no) predictors and six continuous input variables of the targets “mean fear” and “mean disgust” as shown in Table 3.

Predicting Fear

Our first ML model was able to explain 71.8% (*Mdn* = 72.9, *SD* = 7.3) of the variance of the target “mean fear” as compared to -16.7% (*Mdn* = -14.1, *SD* = 1.5) variance of a chance prediction ($p < .001$). The negative R^2 values of a chance prediction indicate a model fit that is worse than trivial fit.

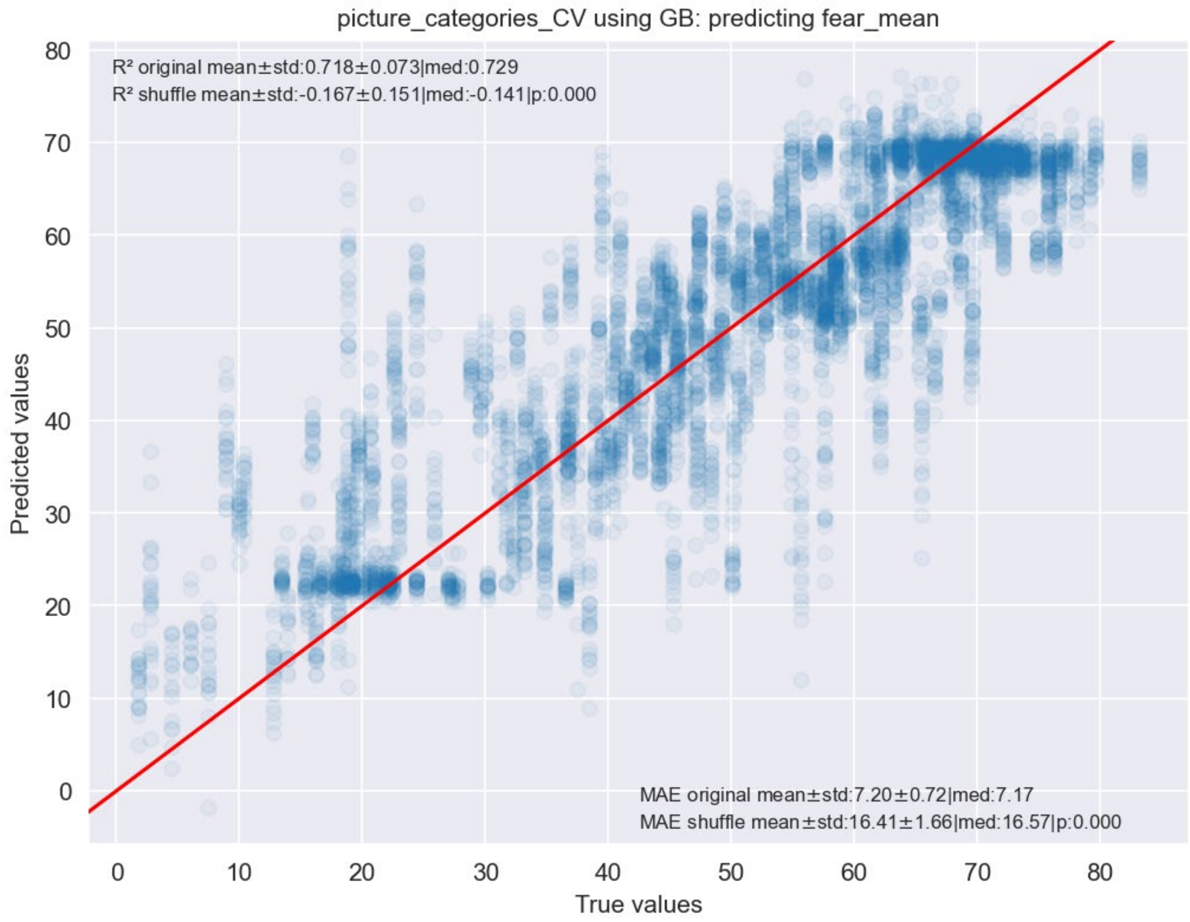
The MAE, the average of the absolute difference between the actual and predicted values, of our first model is 7.20, meaning predictions being possible with a precision of ± 7.20 points (*Mdn* = 7.17, *SD* = 0.72) as compared to a precision of 16.41 points (*Mdn* = 16.57, *SD* = 1.66) of a chance prediction on the rating scale of the target “mean fear” from 0 to 100 ($p < .001$). Therefore, our model was able to predict the target value approximately 9 points better than a prediction by chance as illustrated in Figure 4.

According to the SHAP analysis, the following features have the highest prediction impact on the target “mean fear”, as illustrated in Figure 5 and 6:

- Subjective_size_3.0: Subjective size of spider is large.
- Spider_in_picture_1.0: Spider in picture.
- Subjective_size_1.0: Subjective size of spider is small.
- Texture_of_spider_2.0: Spider has hairy texture.

Figure 4

Model fit of the prediction of "mean fear" using Gradient Boosting

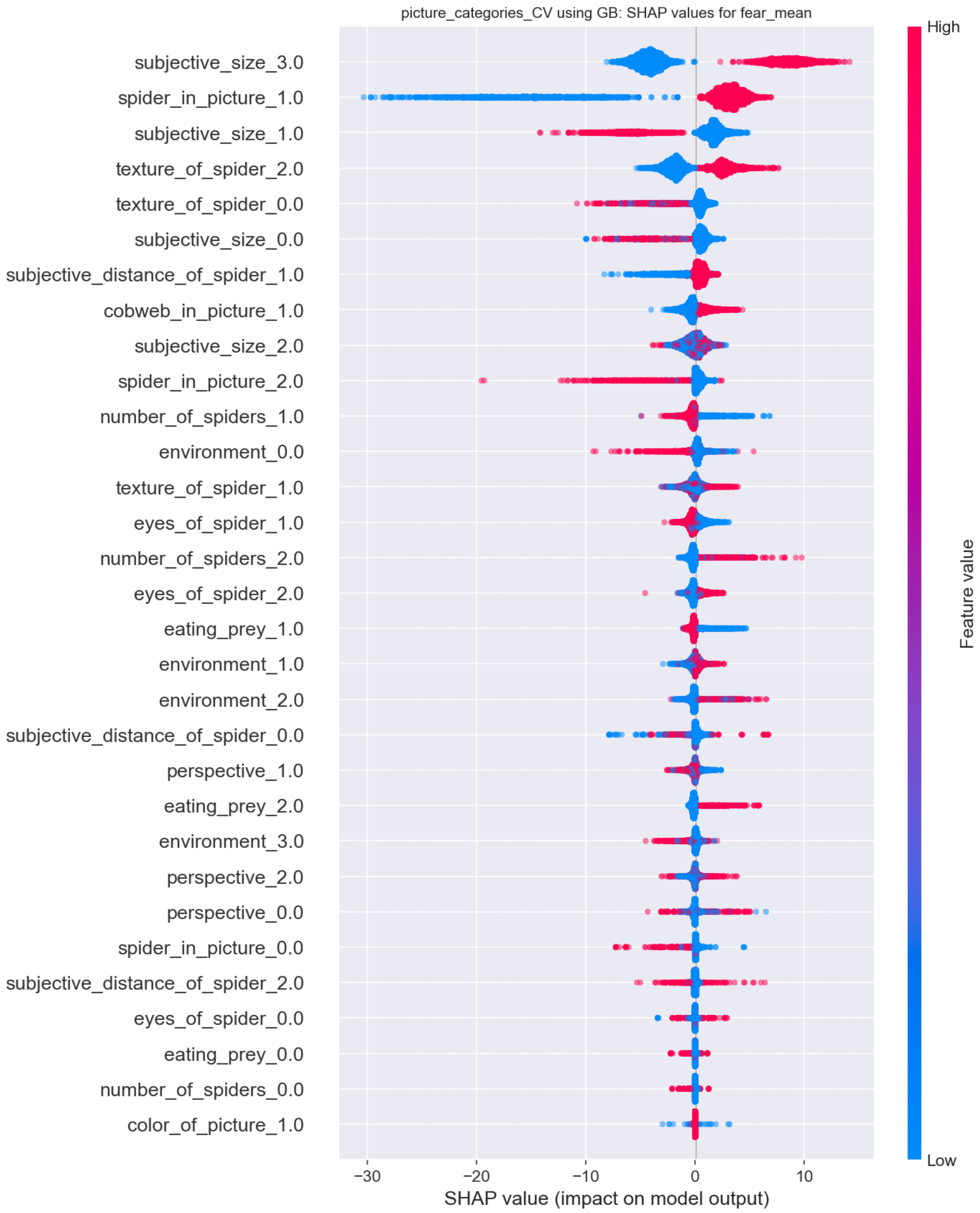


Note. Illustration of the model fit of the GB regression predicting the target "mean fear" plotting the predicted against the true mean fear values. Our model was able to explain 71.8% of the variance of the target. MAE is 7.2 points as compared to a precision of 16.41 points of a chance prediction.

picture_categories_CV = cross-validated data; GB = gradient-boosting; fear_mean = mean fear values; R^2 = coefficient of determination; std = standard deviation; med = median; MAE = mean absolute error

Figure 5

SHAP values illustrating the predictors for the "fear" model

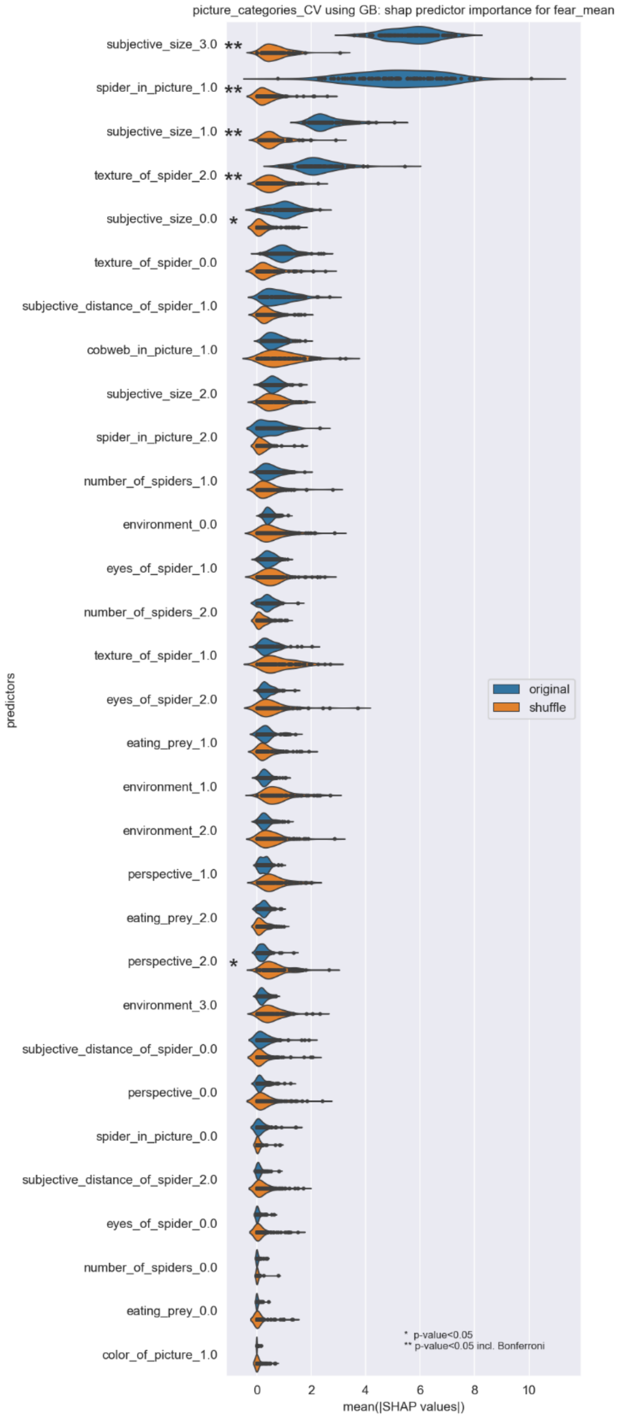


Note. Illustration of the SHAP values depicting the predictors for the target "mean fear" within the GB regression model. Red color indicates high feature values and clue color indicates low feature values. The most important predictors for the target "mean fear" were subjective size of the spider (small vs. large), presence of a spider in the picture and hairy texture of the spider.

picture_categories_CV = cross-validated data; GB = gradient boosting; SHAP = shapely additive explanations; fear_mean = mean fear values

Figure 6

SHAP predictor importance for the "fear" model



Note. Illustration of the SHAP predictor importance of the "fear" model. The attributes "small", "large", "spider in picture" and "hairy texture" were statistically significant within the model as compared to chance prediction.

picture_categories_CV = cross-validated data; GB = gradient boosting; SHAP = shapely additive explanations; fear_mean = mean fear values

Predicting Disgust

Our second ML model was able to explain 72.0% (*Mdn* = 72.7, *SD* = 6.6) of the variance of the target "mean disgust" as compared to -13.7% (*Mdn* = -14.0, *SD* = -1.4) variance of a chance prediction ($p < .001$). The negative R^2 values of a chance prediction indicate a model fit that is worse than trivial fit.

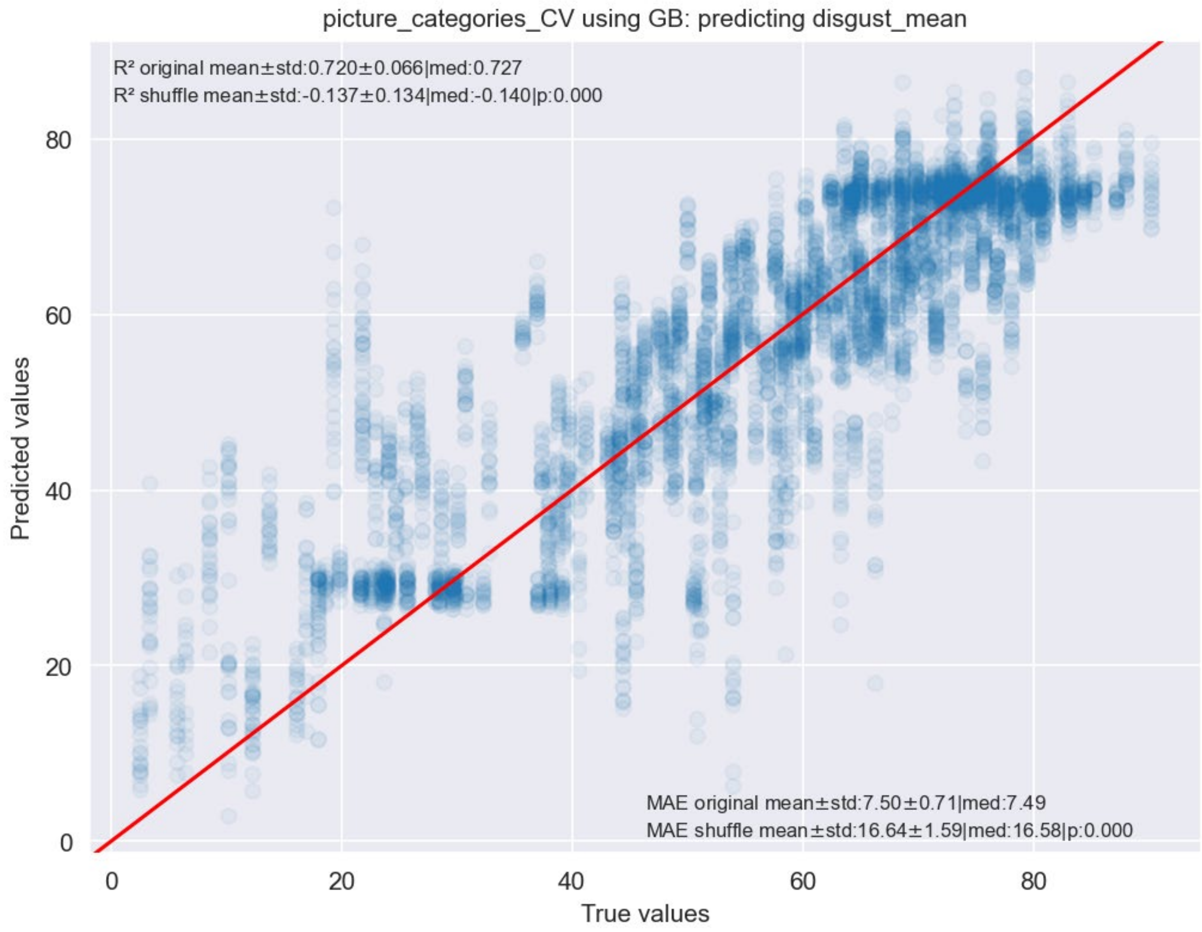
The MAE, the average of the absolute difference between the actual and predicted values, of our second model is 7.50, meaning predictions being possible with a precision of ± 7.50 points (*Mdn* = 7.49, *SD* = 0.71) as compared to a precision of 16.64 points (*Mdn* = 16.58, *SD* = 1.59) of a chance prediction on the rating scale of the target "mean disgust" from 0 to 100 ($p < .001$). Therefore, our model was able to predict the target value approximately 9 points better than a prediction by chance as illustrated in Figure 7.

According to the SHAP analysis, the following features have the highest prediction impact on the target "mean disgust", as illustrated in Figure 8 and 9:

- Spider_in_picture_1.0: Spider in picture.
- Subjective_size_3.0: Subjective size of spider is large.
- Subjective_size_1.0: Subjective size of spider is small.
- Texture_of_spider_2.0: Spider has hairy texture.

Figure 7

Model fit of the prediction of "mean disgust" using Gradient Boosting

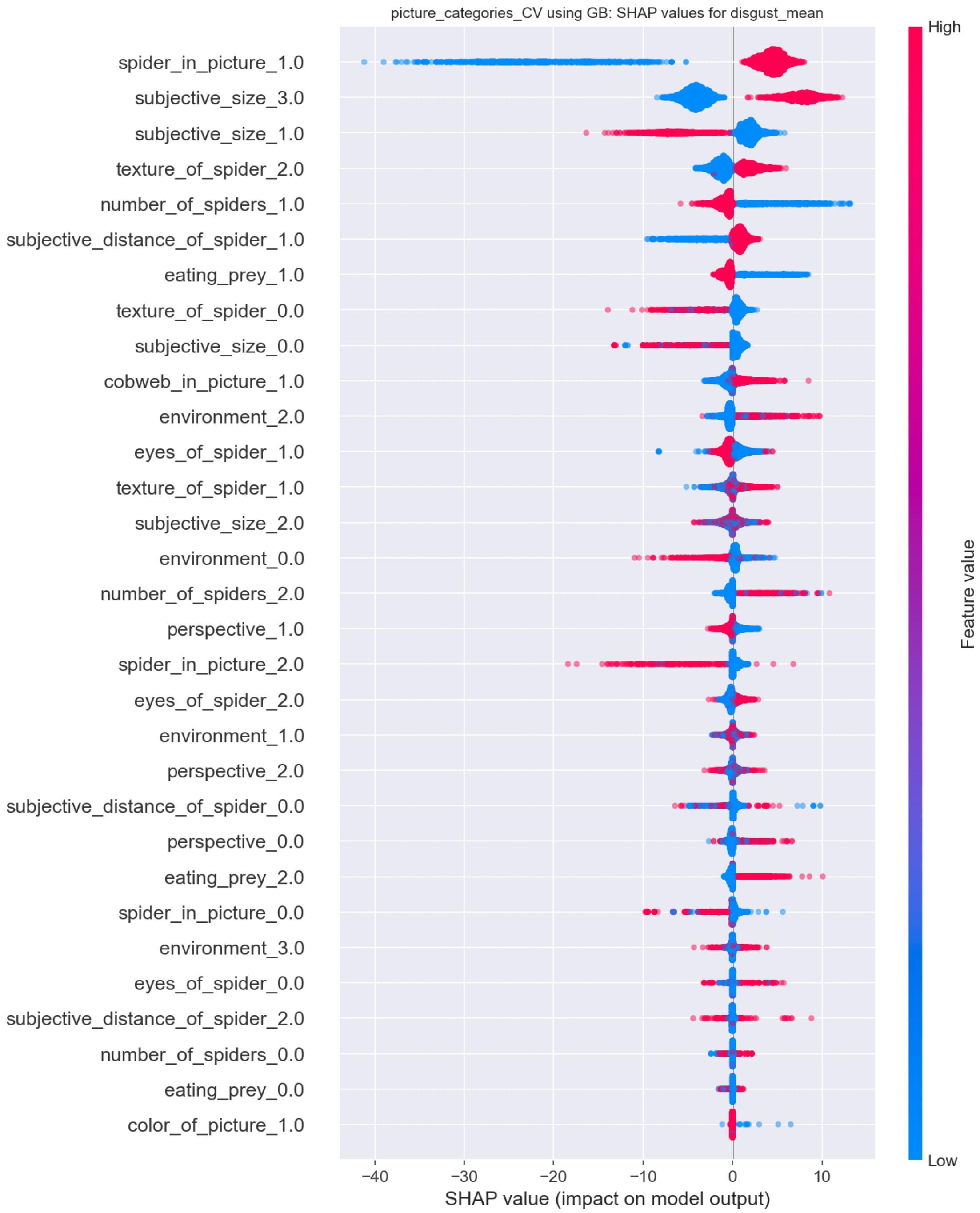


Note. Illustration of the model fit of the GB regression predicting the target "mean disgust" plotting the predicted against the true fear values. Our model was able to explain 72.0% of the variance of the target. MAE is 7.5 points as compared to a precision of 16.64 points of a chance prediction.

picture_categories_CV = cross-validated data; GB = gradient boosting; disgust_mean = mean disgust values; R^2 = coefficient of determination; std = standard deviation; med = median; MAE = mean absolute error

Figure 8

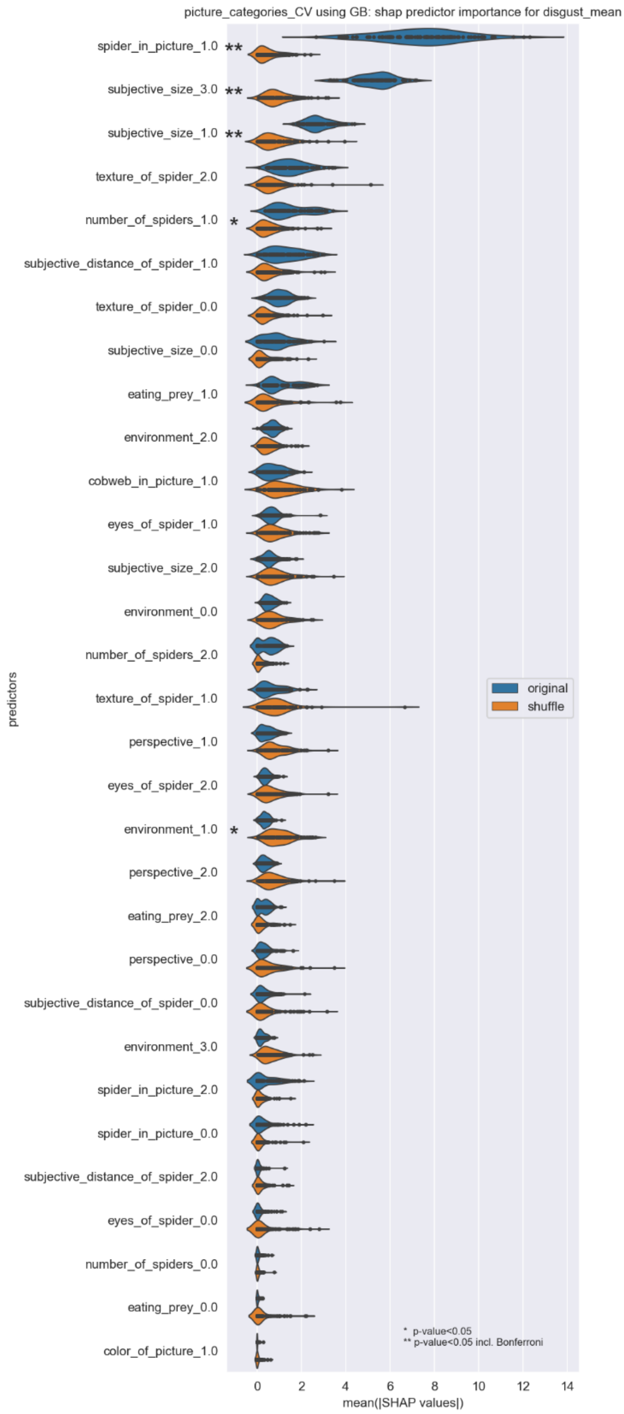
SHAP values illustrating the predictors for the "disgust" model



Note. Illustration of the SHAP values depicting the predictors for the target "mean disgust" within the GB regression model. Red color indicates high feature values and clue color indicates low feature values. The most important predictors for the target "mean disgust" were presence of a spider in the picture and subjective size of the spider (small vs. large). picture_categories_CV = cross-validated data; GB = gradient boosting; SHAP = shapely additive explanations; disgust_mean = mean disgust values

Figure 9

SHAP predictor importance for the "disgust" model



Note. Illustration of the SHAP predictor importance of the "disgust' model. The attributes "small", "large" and "spider in picture" were statistically significant within the model as compared to chance prediction.

picture_categories_CV = cross-validated data; GB = gradient boosting; SHAP = shapely additive explanations; disgust_mean = mean disgust values

Discussion

Spider phobia is one of the most prevalent anxiety disorders in children as well as in adult individuals (Ollendick, 1983; Schienle et al., 2005; Polák et al., 2020). People suffering from spider phobia experience exaggerated, persisting fear, and may even be impaired of functioning in their daily life (American Psychiatric Association, 2013). Previous studies have shown that this aversion towards spiders is associated with the feeling of fear as well as with the sensation of disgust (Abramowitz et al., 2019; Cisler et al., 2009; Davey, 2011; Matchett & Davey, 1991). While fear is considered as an activation of the Defensive Behavioral System protecting individuals against potential threats, disgust could be an evolutionary result of certain animals to be associated with the spreading of diseases, rather than them being truly harmful (Davey, 2011; Fanselow, 1991; Fendt & Fanselow, 1999; Izard, 1977; Marzillier & Davey, 2004; Matchett & Davey, 1991). Both sensations contribute to spider phobia and seem to be confounded (Huijding & de Jong, 2007; Woody & Teachman, 2000).

Exposure therapy is considered as the gold standard for treating spider phobia and is based on controlled exposure to the feared stimulus (Davis et al., 2006; Leuchter et al., 2022). Investigating the visual cues for perceived fear and disgust towards spiders is crucial for the development of efficient exposure therapy concepts, including novel VR settings. However, research regarding fear- and disgust-inducing cues is very limited.

Therefore, the aim of this study was to identify the key aspects of spider images that trigger feelings of fear and disgust in spider-fearful individuals. Using GBDT, we hypothesized to be able to predict “mean fear” and “mean disgust” on a scale between zero and 100. Considering the lack of research, our intention was to provide new evidence and encourage further investigations.

For the purpose of this study, the Spider Images Database (SpiDa) was used. The database consists of 313 images of spiders of various sizes, species, and textures. Within an online survey *N*=152 spider-fearful participants rated the levels of “fear” and “disgust” of these images.

For the analysis of fear- and disgust-inducing cues, five non-spider-fearful members of the research team categorized all images of SpiDa regarding visual features such as texture, subjective size, subjective distance, perspective, and visibility of eyes. On average, 70.4%

(*SD* = 21.2, *range* = 36.7-96.2) of the images were allocated to the same attribute within a category by all five study team members, 16.5% (*SD* = 10.1, *range* = 3.5-29.0) of the images were allocated to the same attribute by four study team members and 13.1% (*SD* = 11.7, *range* = 0.3-36.7) of the images were allocated to the same attribute by three study team members. Categorization was not conducted with images in randomized order. For future studies, randomization should be established to rule out biases.

For the ML analysis, we used GBDT regression as the predictive algorithm between the targets “mean fear” and “mean disgust” and the predictors, represented by the categorization data obtained for this study. The data was used to train two different ML models for the targets. The aim was to predict “mean fear” and “mean disgust” on a scale between zero and 100.

On average, our ML models were able to explain 71.8% (*Mdn* = 72.9, *SD* = 7.3) and 72.0% (*Mdn* = 72.7, *SD* = 6.6) of the variance for the target variables “fear” and “disgust”, respectively. Furthermore, our models were able to predict the values of “mean fear” and “mean disgust” with an MAE of 7.20 (*Mdn* = 7.17, *SD* = 0.72) and 7.50 (*Mdn* = 7.49, *SD* = 0.71) points as compared to 16.41 (*Mdn* = 16.57, *SD* = 1.66) and 16.64 (*Mdn* = 16.58, *SD* = 1.59) points of a chance prediction on a scale between 0 and 100, respectively.

The SHAP analysis indicated that the size of the illustrated spider has a significant impact on perceived feelings of fear as well as disgust, whereas the presence of body hair of a spider was only predicting fear values significantly, but not values of disgust.

Previous studies found similar evidence with the size of the spider representing a central cue for both fear and disgust levels (Lindner, 2019; Zvarikova et al., 2021). Especially an enlarged abdomen was associated with fear and disgust in the study of Zvarikova et al. (2021). Interestingly, the presence of visible body hair showed a significant impact on both fear and disgust values in the study of Zvarikova et al. (2021), whereas our data only indicates a significant prediction of fear values.

Additionally, the data of Zvarikova et al. (2021) as well as of Lindner et al. (2019) showed that longer legs and movement of legs were associated with perceived fear. Within our investigations, the category ‘perspective’ could be comparable, since it includes the attributes ‘from top/bottom’, indicating that all legs of the spider are visible as opposed to the attribute ‘from side/front’, indicating that not all legs are visible. Our data did not reveal any significant impact on perceived fear or disgust.

Visible chelicerae were associated with both fear and disgust levels in the study of Zvarikova et al. (2021); however, this attribute was not part of our investigation. Presence of eyes did not lead to any significant findings throughout both our study and the study of Zvarikova et al. (2021).

Notably, Lindner (2019) did not use images of spiders to investigate aspects related to aversion against spiders but utilized impact ratings to assess which features contribute to situational fear of spiders of the participants. Zvarikova et al. (2021) used one base image and altered it to emphasize certain body parts like abdomen, legs, and eyes.

However, both studies show comparable results which is also partially consistent with our data. These findings contribute to the development of individualized exposure therapy concepts. For instance, for patients whose aversion towards spiders is based on fear rather than disgust, images with fear-inducing features could lead to better treatment outcomes than images with disgust-inducing attributes.

Limitations and Future Directions

Zvarikova et al. (2021) presented interesting data regarding gender differences, as female participants were more likely to be afraid of hairy spiders and spiders with visible chelicerae than male participants. We did not include gender differences in our analysis, since our main goal was to identify visual triggers for fear and disgust. To train our ML models, 80% of the data from our sample of N=152 participants, combining both genders. Therefore, our approach did not focus on possible gender differences. Furthermore, our sample mainly consisted of female participants, with only approximately 18% male participants. However, the gender distribution of the sample of Zvarikova et al. (2021) was very similar, with approximately 78% female and 22% male participants.

For future studies, it would be interesting to include the investigation of gender differences with samples that are uniformly distributed regarding gender to gain further knowledge regarding the impact of gender.

Furthermore, ML methods can be a huge benefit for developing individualized interventions. For instance, for patients whose aversion towards spiders is based on disgust rather than on fear, images with more disgust-inducing features could be used. ML studies cannot only help us to identify the visual cues triggering aversion towards spiders, but also enable us to design tailor-made VR spiders by using generative algorithms that could be utilized for personalized treatments, thus, increasing efficiency of exposure therapy (Mahmoudi-Nejad, 2021).

Extending the range of treatment options could potentially increase the number of suffering individuals seeking help. VR-based approaches could especially encourage younger generations and increase their motivation to seek help to overcome their fears. In the future, individualized VR exposure therapy could also be offered at a more favorable and affordable price, which would appeal to a wider audience, since therapists would be needed to a lesser degree than in conventional exposure therapy settings.

Since previous studies have shown a positive therapeutic effect of VR exposure therapy, further research in this area is recommended (Lindner et al., 2020).

In our analysis, most of the features that were included did not show a significant impact on “mean fear” or “mean disgust” ratings. Future studies should focus on the significant features shown in previously published studies to investigate, whether this could lead to even more accurate predictions of “mean fear” and “mean disgust”.

Furthermore, this approach could possibly reveal differences between “mean fear” and “mean disgust”, that did not appear in previous studies.

Since both Linder et al. (2019) and Zvarikova et al. (2021) found evidence for a significant impact of appearance and movement of the legs of the spider, it would be interesting to include that in future studies, although our data did not show significant results.

Conclusion

Research indicates that spiders can be associated with “fear” as well as with “disgust” (Abramowitz et al., 2019; Cisler et al., 2009; Davey, 2011; Lindner et al., 2019; Matchett & Davey, 1991; Zvarikova et al., 2021). This is in line with our findings, which show quite similar results for both targets “mean fear” and “mean disgust”, except the attribute “hairiness”, which was only significant for the target “mean fear”.

Additionally, our analysis supports evidence from previous studies, that the size of the spider as well as the visible presence of body hair are key attributes that contribute to elevated levels of perceived fear as well as disgust towards images of spiders in spider-fearful individuals (Linder et al., 2019; Zvarikova et al., 2021).

Thus, our research findings contribute to laying the foundation for improved and individualized exposure-based treatments. Increasing the understanding of the underlying mechanisms and visual triggers of spider phobia and aversion towards spiders in general is crucial for making exposure therapy more efficient. Specifically using individualized stimuli that disgust- and/or fear-inducing could lead to better treatment outcome and increase the number of affected individuals seeking help. Automated and individualized VR-based exposure therapy could not only improve treatment outcomes, but also reduce costs and therefore address a broader audience.

Further research will enable us to extend our knowledge about the visual cues contributing to spider phobia and to provide more efficient and individualized treatment options to people suffering from spider phobia.

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