Predictive modeling of optimism bias using gray matter cortical thickness

Raviteja Kotikalapudi^{1,2 *}, Dominik A. Moser¹, Mihai Dricu¹, Tamas Spisak², Tatjana Aue^{1 *}

¹Institute of Psychology, University of Bern, Fabrikstrasse 8, 3012 Bern, Switzerland

²Department of Neurology, University Hospital Essen, Hufelandstrasse 55, 45147 Essen, Germany

***Corresponding authors**

raviteja.kotikalapudi@uk-essen.de

(or)

tatjana.aue@psy.unibe.ch

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Conflict of Interest

The authors declare no conflicts of interest.

Data availability

The data is available upon reasonable request.

Summary

1. To our knowledge, this study is the first attempt at predictive modeling for optimism bias using gray matter cortical thickness.
2. Our model significantly predicts optimism bias with Pearson's $r = 0.41$, p -value = 0.007, tested for 10,000 surrogate combinations.
3. The main predictive regions include left rostral and left caudal anterior cingulate gyrus, right pars orbitalis and entorhinal cortex, predominantly negatively correlating with personal optimism bias.
4. More of such predictive models on a large-scale data platform are needed, to help us understand positive psychology and individual well-being.

Abstract

Optimism bias (OB) is an expectancy bias, where people expect irrationally good future outcomes for themselves. Predictive modeling for OB would open new opportunities for estimating an overall state of well-being and understanding clinical conditions such as depression. To our knowledge, this is the first study attempting to address OB implementing a dedicated machine-learning based predictive modeling. We calculate people's OB via a soccer paradigm, where participants rate their comparative chances for a successful outcome against their rival (i.e., personal OB) and a rival team (social OB). Later, using gray matter cortical thickness (CT) in a machine-learning framework, we predict both POB and SOB. Our results reveal a significant brain structure-based predictive model for experimentally assessed POB (Pearson's $r = 0.41$, $p = 0.007$). Strongest predictors include left rostral and caudal ACC, right pars orbitalis and entorhinal cortex, all shown to have a role in OB before. Our confounder analysis suggests that the predictions are predominantly driven by CT measures and are not corrupted by demographic data (e.g., age and sex). There were no predictors recognized for estimating SOB. More of such predictive models on a large-scale data platform are needed, to help us understand positive psychology and individual well-being.

Introduction

Optimism bias (OB) is a well-established behavioral dimension, where individuals associate themselves with more positive outcome scenarios than negative [1, 2]. More specifically, optimism bias can further be branched into the deeper concepts of personal and social optimism biases [3]. Personal optimism bias (POB) stems from a bias towards oneself where an individual expects a more favorable outcome compared to a peer or competitor, given the same scenario. For example, ‘I have better chances to be accepted for this job position than the fellow competitor’. On similar grounds - yet different - social optimism bias (SOB) is manifested in comparing successful outcomes for one’s own (or preferred) social group when compared to their rival social group. An example could be, ‘my favorite soccer team will likely win at tonight’s match’. Both, POB and SOB can be quantified as the difference in the likelihood estimated for a positive outcome for *self (in-group) versus rival (out-group)*, where positive estimates index the presence of OB. The presence or absence of such a bias is quantified by psychological questionnaires, for example the comparative optimism scale [1], as well as through experimental paradigms [4-7].

Psychological evaluations through behavioral questionnaires and experimental results may validly and reliably reveal OB. For a more comprehensive picture, studies have also investigated neural correlates of OB, predominantly using fMRI. For example, studies have reported an active role of anterior cingulate cortex, ACC [8-10] and ventromedial prefrontal cortex, vmPFC [9, 11]. Other important areas include the orbitofrontal cortex (OFC), posterior cingulate gyrus (PCC), striatum, and insula [4, 9, 11]. But very few studies have directly probed into the neuroanatomical association of OB or related constructs via structural MRI using T1-weighted images. For example, participants in a recent study [12] performed an expectancy task that addressed optimism robustness, which is expressed by greater attentional guidance by optimistic rather than pessimistic cues). We found that gray matter volume (GMV) of the ACC, bilateral insular, and primary visual cortex, all correlated with optimism robustness [12]. Using a related concept of belief update (preferential updating of future expectancies for pieces of information that support an optimistic rather than pessimistic view of the own future), a study has reported only in older recruits, that GMV of ACC linked with OB [13]. But this phenomenon was not observed in the same study, in the younger population. While these studies thoroughly investigated the role of brain structure and function in concepts underlying OB, it is still unclear as to what is the predictive yield of these structures towards OB.

Studying such predictive yield is worthwhile because it may enable the identification of the most important structural brain characteristics (e.g., of identified key regions in earlier research, such as ACC, insula, striatum, and PCC) to the strength of the manifested OB. Lai et al. have addressed this issue to some extent in their study, where bilateral GMV of putamen correlated with trait optimism (i.e., the tendency to look positively into one’s own future, which is not necessarily irrational as in OB) [14]. However, their primary findings were based on voxel-based morphometry with behavioral questionnaires of the life orientation test (LOT, as an indicator for trait optimism), and its results were only then confirmed by a predictive approach, as a post-hoc reliability strategy. Hence, unsupervised predictive modeling was not the primary choice of analysis. Yet, such studies always remain as an important step towards robust predictive modeling using dedicated machine-learning approaches. Importantly, by forming a predictive model for OB, we can enhance these frameworks to better explain the structure-driven psychological state of well-being, as OB and related concepts have been shown to be closely linked with individual well-being [15-17]. Not only that, but a predictive marker for OB can also find potential applications in understanding neural substrates of depression, post-treatment recovery and acute-chronic pain states, all of which have been strongly linked to OB and similar concepts [16, 18-22]. Such an approach may thus inspire deeper clinical and psychological applications.

In our study, we aimed at deriving such a predictive model using well established and reliable measures of gray matter cortical thickness, exclusively utilizing a machine-learning framework. Gray matter cortical thickness remains the feature set for the predictive modeling, and POB and SOB serve as the target variables. Both, POB and SOB were calculated from a previously established soccer-based experimental paradigm [3, 4, 23]. In brief, each participant recruited for our experiment was asked to estimate the likelihood for successful outcomes given different soccer

situations (**figure 1**). Most importantly, the participant would give these likelihood estimates for the self, a personal rival, an in-group (a favorite team) and an out-group (rival team). POB was quantified as the difference in estimates for self-versus rival, and SOB was quantified as the difference in estimates for in-group versus out-group. The neuroanatomical parameters were trained using a linear model in a machine-learning framework, to predict both POB and SOB. Overall, our approach was aimed at finding the true predictive value of gray matter cortical thickness in explaining OB. We examined both POB and SOB to identify potential overlapping brain-structural similarities and divergences between the two.

Figure 1. Soccer task.

At the start of each trial, a fixation cross was presented for a duration of 2 to 3 seconds (variation due to jittering). Next, a player representing the self, rival, in-group, or out-group was displayed for 2 seconds. Subsequently, a soccer game scenario was presented for 10 seconds; in this latter phase participants estimated the likelihood for a successful pass (rating range 0 – 100%). Each trial lasted approximately 15 seconds.

Methods

Participants: Our study takes leverage from Moser et al. [3], who investigated functional brain correlates of optimism biases. We have used the same dataset in terms of participants, experimental setup, and deriving the optimism biases. But, while Moser et al. investigated the functional correlates for optimism biases, we use the structural MRI images in a machine-learning framework for predictive modeling of optimism biases. In brief, we recruited 46 participants (34 females) at the University of Bern, Switzerland through flyers, emails, and the local participant pool. The recruited participants' age group was in the range 19 - 35 years (mean = 22.9, std = 3.62). Exclusion criteria for the recruitment were self-reported neurological disorders, psychoactive substance abuse and left-handedness. The experiments were recruited by the local ethics committee and all participants gave a written consent in accordance with the guidelines of the Declaration of Helsinki. Participants were paid either 25 CHF/hour or obtained course credits.

Experimental setup: The experimental participation took place inside an MRI scanner (3T Magnetom, Prisma from Siemens, Erlangen, Germany) and the task was designed using e-prime 2.0 Professional (Psychology Software Tools, Sharpsburg, PA, USA). The task cartoons were created with The Sims 4 (Electronic Arts, Redwood City, California, USA) and the soccer scenarios with Photoshop CS6 (Adobe Inc., San Jose, California, USA). Visual projection of the task was enabled by an LCF projector (PT-L711E, Panasonic, Kadoma, Japan). The task's duration was approximately 30 minutes. Moser et al. (Moser et al. 2021) gives a detailed description of the experimental paradigm, which has been adapted from a similar experiment on American football [4]. Participants were trained on this experiment before the actual task was conducted. In brief, the participants were shown four different characters who faced 16 identical soccer scenarios. The four characters refer to (a) the self (where participants consider themselves to be confronted with a given scenario), (b) a personal rival (participants consider a personal competitor for their own position in their soccer club undergoing that same scenario), (c) an in-group (consideration of a player from a team the participants identify with), and (d) an out-group (consideration of a player from the in-group's rival team). Given these characters and scenarios, the participants' task was to estimate the likelihood for a successful pass (i.e., passing the ball to a fellow

team player), or a successful goal. The likelihood estimates were given by button presses that shifted a slider on an analogue scale that ranged from 0 (certain of an unsuccessful outcome) to 100 (certain of a successful outcome). The task was performed in two blocks (a + b and c + d) with randomized trials (16 scenarios for each character) within each block. Using the likelihood estimates, four raw scores (for self, rival, in-group, and out-group) and two derived scores of optimism biases were calculated (personal optimism bias = self - rival, where positive value indicates the presence of a personal optimism bias; social optimism bias = in-group - out-group, where a positive value indicates the presence of a social optimism bias).

Features and targets: The T1-weighted anatomical scans were independently processed using freesurfer version 6.0 (<https://freesurfer.net/>, [24, 25]) to obtain cortical thickness measures of 34 regions from each of the hemispheres (total = 68). The cortical thickness measures were estimated in the native space according to the Desikan-Killiany anatomical atlas [26]. These regions across all participants served as the feature set in the machine-learning (ML) framework. The targets were POB and SOB. The features and targets were used to derive a predictive model for the OBs, via a robust ML framework.

Machine-learning framework: The ML framework was designed using scikit-learn (<https://scikit-learn.org/stable/>, [27]) via python implementation. We performed a nested cross-validation (CV) utilizing the feature and the target datasets. The nested CV approach ensures that the performance of the model is tested on the data that was not seen during model fitting, minimizing data leakage and overfitting. The entire framework was split into two CV schemes, i.e., the outer CV and the inner CV. The outer CV was used for the purpose of obtaining unbiased predictions of the target using the best model estimator, whereas the inner CV was performed to derive the best model estimator. The model that we used was LASSO (least absolute shrinkage and selection operator) regression, which is based on adding an L1-penalty to the linear regression, for the purpose of a better generalization. Our main purpose of applying the LASSO model was for an easy interpretation of the results, as LASSO shrinks non-relevant features by assigning a zero weight. The best model estimator (inner CV) was selected by tuning the scaling factor α , which scales the L1-regularization. The values tested for α = [0.0001, 0.001, 0.01, 0.1, 10, 100, 1000], and the selection of the best α was based on mean squared error as the cost function. For both model selection (inner CV), as well as final predictions (outer CV), data was split using leave-one-out CV. All associations were tested for Pearson's r , with p-value calculated based on 10,000 surrogate combinations. Finally, a confounder test was performed between the predictions and age, sex, as well as TIV using permutation testing. If there was an association between the predictions and the potential cofounders, they were regressed out using a linear regression model with the CV-stream, to make sure that the predictions were exclusively driven by features of importance (cortical thickness in our case). Along with the nested CV approach, a non-nested CV framework was also performed. The non-nested CV consisted of only the inner CV (hyperparameter tuning), and the final predictions were made with the best LASSO estimator using `cross_val_predict` in a leave-one-out CV approach.

Results

Behavioral results: We performed outlier detection on the target variables (i.e., POB and SOB) and rejected the participants whose scores were $> 3SD$ from mean. This resulted in a total of 45/46 participants qualifying for the final analysis. The behavioral demographics are displayed in **figure 2**. To check our hypothesis that POB (= self $>$ rival) and SOB (= in-group $>$ out-group) manifests, we performed a paired t-test for both the contrasts. Both POB ($t(44) = 2.97$, $p = 0.002$) and SOB ($t(44) = 2.96$, $p = 0.002$) were significant. There were no significant differences between POB versus SOB ($t(44) = 0.462$, $p = 0.646$).

Figure 2. Behavioral data.

(a) Behavioral data for the raw scores (self, rival, in-group, and out-group) and (b) the derived measures (POB, SOB) are presented. * Indicates a significant difference in the means ($p < 0.05$). Derived measures are POB = self - rival, and SOB = in-group - out-group, where POB stands for personal optimism bias and SOB for social optimism bias. Both POB and SOB are referred to as targets in the machine learning framework. Error bars represent standard errors.

Machine-learning results: The ML results were generated using a nested cross-validation framework using a LASSO linear regression model. The working details are presented in the methods section. The structural MRI derived cortical thickness measures comprised of 68 features (34 bilateral regions) served as the feature set, whereas POB and SOB were the targets that were predicted using the linear model.

For POB predictions, the best LASSO model was found to be with regularization factor $\alpha = 0.1$. The unbiased estimates (predictions) correlated with the target with Pearson's $r = 0.41$, $p = 0.006$. The prediction versus target and predictors and their significant weights are presented with **figure 3** and **table 1** respectively. Significant negative weighted regions (cortical thickness of predictive regions that correlated significantly with POB at $p < 0.05$) were the left rostral anterior cingulate (rACC), left caudal anterior cingulate (cACC) and right pars orbitalis. The significant positive weighted region was the right entorhinal cortex. The predictions did not correlate significantly with age, sex or TIV, thus eliminating potential confounding effects. While the final predictions were free from confounding effects of age, sex and TIV, **supplementary table 1** also shows the effect of confounders in predicting optimism bias. For instance, if not corrected for age, the predictions significantly correlated with age (Pearson's $r = 0.34$, $p = 0.02$). Predictions with the non-nested CV are also presented, with **supplementary figure 1 – supplementary table 2**. In brief, both nested and non-nested CV resulted in similar predictions. There were no significant predictions for SOB.

Figure 3. Predictions for personal optimism bias (POB).

(a) The scatter plot with regression line is presented for prediction versus actual POB scores, (b-e) indicate predictive regions. For b-e, age was regressed out from each of the regions. 10,000 surrogate combinations were tested to generate the p-value for the Pearson's r .

Table 1. Weights of nested cross-validation best estimator (unbiased model).

Regions	Weights
left rostral anterior cingulate (rACC)	-10.59
left caudal anterior cingulate (cACC)	-3.84
right pars orbitalis	-0.30
left entorhinal	-0.05
left isthmus cingulate	0.00
left pericalcarine	0.01
right frontal pole	0.02
right postcentral	0.55
right entorhinal	1.75
left parahippocampal	2.73

'-' sign indicates a negative correlation of the corresponding region with POB. '+' sign indicates a positive correlation of the corresponding region with POB. Left rACC, left cACC, right pars orbitalis and right entorhinal cortex also correlated significantly with personal optimism bias (POB).

Discussion

In this paper, we describe a predictive model for OB in a machine-learning framework, using gray matter cortical thickness and experimentally derived scores of personal and social optimism biases (POB and SOB respectively). The model significantly predicts POB with Pearson's $r = 0.41$ ($p = 0.006$, permutations = 10,000). The Pearson's r is in the small to medium range in terms of its effect size. The key predictors include the left rostral anterior cingulate cortex (rACC), left caudal anterior cingulate cortex (cACC), right pars orbitalis and right entorhinal cortex. The predictions were exclusively driven by cortical thickness and not confounded by the measures of age, sex, and total intracranial volume (TIV). Our predictive model hence reveals important brain structural associations with OB and is a step towards (a) predictive modeling of such biases. Moreover, the current findings may (b) inspire clinical applications for mental disorders like depression and increase our understanding of psychological well-being.

Model considerations: First, we have used the derived measures of POB and SOB as target variables in our predictive modeling, thus, two different kinds of OB to compare potential brain-morphological similarities between them. Second, the paradigm implemented to derive these biases has been validated previously [3, 4, 23]. Third, as a feature set, we considered gray matter cortical thickness for predicting optimism bias. One strong reason favoring such a selection is that cortical thickness is a robust and reliable measure widely used in neuroimaging studies, and requires minimal feature scaling and residualization (e.g. cortical thickness measures are not driven by TIV), thereby facilitating a simpler and reliable interpretation of the findings [28, 29]. Forth, confounding effects play a crucial role in predictive modeling, as the model can learn from the confounders. For example, while the residualization methods vary across studies, removing confounder effects from the initial feature set as a standard protocol do not guarantee a confounder-free prediction due to the inadequacy of such residualization methods [30]. Hence, we regressed out the confounding variables from the final predictions (unbiased estimates), thereby providing a clear bifurcation of predictions into (a) predictions with confounder effects and (b) predictions free from confounding effects. Here, it is worth mentioning that the regression of confounders was performed within the nested CV to avoid data leakage. Fifth, regular linear regression models can be prone to overfitting e.g., in including the final number of features for predicting the dependent variable. This issue can be resolved to an appreciable extent by using the LASSO model [31], which applies a shrinkage to irrelevant variables (by assigns a zero weight through regularization, i.e. by adding a penalty), thereby reducing overfitting and at the same time, increasing the interpretability of the findings. Hence, our selection of the linear model as LASSO was predetermined. Furthermore, using the non-nested CV approach, we kept the training and test datasets separate for model selection and hyperparameter tuning, thereby avoiding any cross-contamination (minimal data leakage) and avoiding 'optimistic' predictions by the model [32]. This is because the data point on which prediction is performed is not used in selecting the best model estimator (i.e., model used to make the estimations / predictions).

Biological relevance: The strongest predictors of our POB model, after regressing out the confounding effects were right rostral and caudal anterior cingulate cortex (ACC). This was followed by right pars orbitalis (orbital part of inferior frontal gyrus, IFG) and right entorhinal cortex. In terms of effect sizes, both parts of ACC (rostral + caudal) were in the medium range. The ACC is reported to play a crucial role in influencing OB and related concepts, as per significant findings from both functional [8-10, 33] and structural studies [3, 12, 34]. For instance, in a concept close to optimism bias, GMV of ACC was shown to correlate negatively with optimism robustness [12]. In this study, optimism robustness was expressed by greater attentiveness towards reward expectation (i.e., optimistic) cues and less towards punishment expectation (i.e., pessimistic) cues. While the task is different to the soccer paradigm in the current study, both address related facets of personal optimism and the (negative) directionality of the link between ACC size and optimism is comparable. Furthermore, in another study, a reduced ACC volume was associated with quality of life, which was acquired with a self-report questionnaire from participants [35], a concept that is positively associated with optimism [36-38]. Both structural and functional studies have indicated an active involvement of ACC in fear and punishment [39, 40], which fits well with the notion that a decreased volume of ACC could be indicative of lower self-referential fear or punishment upon failing. Such observations fit well with our current finding of higher estimates

for one's own successful outcomes against a rival. It thus is possible that a small-sized ACC promotes POB (please note that causality still needs to be proven).

Another region, the right inferior frontal gyrus (orbital part of IFG) was also a negative predictor of POB. This observation provides support to Sharot et al.'s [41] finding for the right IFG which was negatively correlated to optimistic belief updating. In their experiment on optimism bias based on belief updates, BOLD signal in the right IFG was negatively correlated with undesirable error estimates. That is, maintenance of personal optimism went along with decreased brain activity in the right IFG when the informed average probability for a negative event to occur was higher than a participant's estimate and indicated the rejection of learning based on negative feedback. In our study also, we found a negative association between IFG thickness and POB, demonstrating that not only functional but also structural aspects of this area play an important role in positive expectancy biases.

The only significant positive correlation with POB in the current study was found for the right entorhinal cortex, a region that surrounds the hippocampus as part of the hippocampal formation [42, 43]. It is known for communicating neocortical inputs to the hippocampus [44, 45], and is well established for its contributions to memory encoding [46-49]. A positive correlation for this region's thickness with POB might explain a selective encoding and consideration for more positive than negative perspectives, with such regulative actions preventing depression [50].

Finally, remaining left (parahippocampal, entorhinal, isthmus cingulate, pericalcarine) and right hemispheric regions (frontal pole, postcentral) were also assigned non-zero weights by the best estimator LASSO in the POB model. However, individually, these regions did not correlate significantly with POB. Hence, these regions - alone - may not have the predictive capacities towards the target, but together with other regions, they help in predicting POB.

We did not find any regions supporting SOB. The main reason for this could be that the model simply did not retain any of the regional thickness measures as significant, and most importantly as generalizable predictors for SOB. Our data are thus supportive of the idea that POB is more in-built in the human organism than is SOB. It is possible that the SOB only came later during human evolution. While saying so, other structural imaging metrics such as white matter connectivity could prove to be better estimators for such a bias, because SOB is evident from the behavioral aspect (soccer paradigm) and may be explained by a different set of structural markers. Hence, while we see similarities between POB and SOB in some studies [3, 23, 51], the current data outline that there are also clear discrepancies. Here, it is further worth mentioning that previously, using the Stereotype Content Model [52, 53], Moser et al. [51] were able to identify cortical thickness associates for social optimism. However, this investigation differed in various aspects to the current study, including experimental paradigm (e.g., inclusion of various out-groups and positive as well as negative scenarios in the case of Moser et al.) and type of multivariate analysis implementation in use (sparse canonical correlation analysis versus machine-learning based model selection).

Limitations: An external validation with completely unseen data is not present with our study. However, reliability of our findings using both non-nested and nested cross-validation approaches, as well as a previously validated experimental setup [3, 23] for quantification of target variables (both POB and SOB), all add to the predictive confidence of the model. Hence, we expect the model to be generalizable towards newer datasets, though the findings shall be interpreted with caution. In the future, a multi-collaborative research consortium could help in the external validation of our model on newer datasets.

Conclusion: We derived predictive models to predict OB using gray-matter cortical thickness as the feature set, and personal-social levels of optimism (POB and SOB) as the dependent variables. The model predictions significantly correlated with POB, and the predictions were not confounded by factors such as age, sex and TIV. The major predictors for POB were thickness in the left rostral and caudal anterior cingulate gyrus, right pars orbitalis and right entorhinal cortex, predominantly correlating negatively with POB. While the predictive framework was able to estimate POB, a similar result was not achieved in predicting SOB. Our predictive model approach for POB is a step

towards predictive neuroimaging in positive psychology, which could find potential applications in explaining states such as individual well-being, as well as in identifying clinically relevant symptoms for conditions such as acute and chronic depression.

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Supplementary figure 1

A scatter plot with regression line for predictions versus actual observed optimism bias using a non-nested cross-validation is shown here.

Supplementary table 1. Predictions with and without confounding effects.

		Predictions versus Age (r , p)	Predictions versus Sex (r , p)	Predictions versus TIV (r , p)
Predictions with confounding effects	0.45	(0.34, 0.02)	(0.03, 0.8)	(0.06, 0.7)
Predictions without confounding effects	0.41	(-0.01, 0.93)	(-0.04, 0.8)	(0.01, 0.95)

It can be observed that *predictions with confounding effects* are confounded by 'age'. Hence, the potential confounder effects were regressed out from the final predictions, in the nested cross-validation framework, to obtain unbiased estimates of POB.

Supplementary table 2. Weights for the predictive regions using non-nested cross-validation.

Regions	Weights
left rostral anterior cingulate cortex	-10.6
left caudal anterior cingulate cortex	-3.9
right pars orbitalis	-0.04
right postcentral	0.35
right entorhinal cortex	1.8
left parahippocampal gyrus	2.7

‘-’ weight refers to a negative correlation and ‘+’ weight refers to a positive correlation.