A VARIATIONAL-AUTOENCODER APPROACH TO SOLVE THE HIDDEN PROFILE TASK IN HYBRID HUMAN-MACHINE TEAMS

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ABSTRACT

Algorithmic agents, popularly known as bots, have been accused of spreading misinformation online and supporting fringe views. Collectives are vulnerable to hidden-profile environments, where task-relevant information is unevenly distributed across individuals. To do well in this task, information aggregation must equally weight minority and majority views against simple but inefficient majority-based decisions. In an experimental design, human volunteers working in teams of 10 were asked to solve a hidden-profile prediction task. We trained a variational auto-encoder (VAE) to learn people’s hidden information distribution by observing how people’s judgements correlated over time. A bot was designed to sample responses from the VAE latent embedding to selectively support opinions proportionally to their under-representation in the team. We show that the presence of a single bot (representing 10% of team members) can significantly increase the polarization between minority and majority opinions by making minority opinions less prone to social influence. Although the effects on hybrid team performance were small, the bot presence significantly influenced opinion dynamics and individual accuracy. These findings show that self-supervised machine learning techniques can be used to design algorithms that can sway opinion dynamics and group outcomes.

Keywords Social bot · decision-making · hybrid intelligence · hidden profile · team performance

1 Introduction

The effect and influence of minority opinions on social groups have long been studied in psychology and sociology [1, 2, 3, 4]. More recently, public interest in these questions has increased due to media coverage of troll factories,

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social bots and automated accounts on public fora [5, 6]. However, few studies have experimentally measured social bots’ ability to selectively support minority opinions and influence collective outcomes. In this paper, we trained a variational auto-encoder (VAE) to recognize shared information sources among a team of people solving a hidden profile task. We then used the VAE model to program a bot to selectively support minority opinions and quantified the effect on teams opinions and teams accuracy.

The presence of automated accounts, popularly known as social bots, is well documented on social media [7, 8]. Their goals and tasks can vary from innocuous chatbots to more malicious automated accounts [9]. Social media bots, in particular, have been accused of spreading hyper-partisan content to push political agendas and increase the perception of fringe views[10]. Bots may inflate the perception of particular views’ popularity and contribute to the spread of misinformation, conspiratory theories, and partisan messages [11, 5]. Whether bots can be intentionally designed to improve group performance is a matter of debate [12, 13]

Collectives, like groups, teams and online crowds, are vulnerable when information to solve a task is unequally distributed across multiple players [14, 15]. This scenario is known in psychology as the hidden profile problem. Some pieces of information are shared by a majority of players, while other pieces of information are known only by a minority of players (hidden information). The typical finding is that players tend to discuss and use information shared by the majority rather than the (still useful) information available only to minority players. We hypothesized that, in this scenario, artificially supporting minority opinions should improve team performance by rebalancing information distribution in the group. The hidden profile paradigm offers the opportunity to test the effect of a bot supporting minority views in a task where such influence can be beneficial for group outcomes.

Threats (and opportunities) of deploying bots in social networks are more consequential when people’s opinions are aggregated to form collective decisions like during democratic processes and elections, or when opinions are aggregated to forecast future outcomes in economic and geopolitical forecasting. For instance, researchers have documented bots’ potential for distorting information and exerting undue influence on popular opinions in real-world democratic decisions [5, 16, 17, 18]. These concerns have stimulated research on the subject [19, 20, 21, 22] and have mobilized platforms to improve automatic detection and removal of algorithmic accounts [23, 24, 25, 16]. We contribute to this literature by advancing the hypothesis that, in addition to removing malicious bots, an equally effective strategy to combat misinformation is to design bots expressing views that increase opportunities for individuals to be exposed to hidden information.

In this paper, we experimentally study these phenomena in a modified hidden profile paradigm [14, 15]. We asked teams of volunteers to make weather predictions based on random indicators (humidity, temperature and wind speed) with individual predictive patterns, which had to be learned from trial and error. Although outcomes were predicted by a linear combination of all indicator variables, each individual was able to observe only one indicator. Indicators were unequally distributed among the team, with one indicator being shown to the majority of participants (majority group, 50%), while two more being shown to two minority groups (30% and 20% respectively). In each round, participants were asked to give an independent forecast and then revise it based on the forecasts made by others in their team.

We hypothesize that a bot selectively supporting minority views would help team performance by reducing the majority’s influence in this task. Instead of telling the bot whether people held majority or minority information sources, we trained a variational autoencoder (VAE) to learn this representation in an unsupervised fashion, namely from observing the correlation of people’s responses over the first 110 rounds of the game. VAE-based approaches are used in several domains to generate low-dimensional interpretable embeddings from complex data [26]. The use of a VAE allowed us to generate original opinions by sampling from the hidden latent representation layer of the VAE, rather than simply copying of human opinions [25, 27]. Our bot used VAE’s representation of people’s similarity (based on past trials) to strategically position itself on the opinion space. In the last 50 rounds of the game, we replaced a human player in the review stage with the VAE bot. Bot’s responses were inbetween the average majority response and the minority response, but closer to minority views. Thus the bot positioned itself in a region of opinions where people are more susceptible to social influence, sometimes referred to as ‘latitude of acceptance’ [4]. This strategy may be more flexible and adaptive than simple opinion copying because it is adaptive to opinion shifts in humans over time. While current bots may have a significant impact because of their sheer number, strategic adaptive bots may be individually more effective at influencing the social system they are plugged in.

Furthermore, we hypothesized that by adopting opinions between majority and minority views, the bot could bridge the gap between the two opinion clusters and facilitate consensus. We compare the effect of such an adaptive bot with a random bot [28]. We conducted a series of exploratory data analysis that we report below. Our findings suggest that instead of bridging the gap between majority and minority views, the VAE bot further increased the team’s polarisation by making minority views less prone to social influence by the majority. Reduced majority influence was especially true when people were facing challenging rounds, and thus people were more likely to seek social information. The

bot's influence on team performance was relatively weak but followed a similar pattern. In minority groups, the VAE bot improved initial judgments.

2 Methods

Procedure The game was implemented in Empirica [29]. The game's task consisted in predicting a binary weather outcome (Rain vs. No Rain) based on the information provided by independent weather indicators. Participants were tested in teams of ten. Within each team, participants were assigned to one of three weather conditions, either "wind", "temperature" or "humidity". These experimental conditions determined which weather indicator a given participant could see during the game – e.g. participants in the "wind" group could see only the wind measurement on any given round. Indicator assignment was unbalanced: The size of each indicator group was five, three and two participants respectively. Thus, a simple opinion average would have resulted in larger but suboptimal influence of the majority indicator. We randomized which indicator group was assigned to which indicator group size across the thirty games we run.

The training phase had 110 rounds. In each round, a participant could see a measurement ("stimuli") on a percentage scale after which she was asked to predict the chances of rain within a 10 second window. The prediction was provided on a probabilistic scale of 0 to 1, where 1 corresponded to being certain that it will rain and 0 corresponded to being certain that it will not rain. After each round, participants could see the outcome for 5 seconds, and the Brier score calculated from their predictions was added to their score total. We used Brier scores to discourage over- and/or under-confidence. Brier scores were computed as:

$$b = (I - p)^2 + (\neg I - \neg p)^2 \quad (1)$$

Where I is the indicator variable ($I=0$: sun; $I=1$: rain), p is the probabilistic forecast and " $\neg$ " represents the complementary probability.

Figure 1: Experiment Timeline. (a) During the first 110 rounds, participants see measurements from their indicator group and need to provide weather forecasts. On each round they receive feedback ("It rained" vs. "It did not rain"), thus allowing them to learn the predictive relation between the indicator and the outcome. (b) During the interaction phase, after seeing their indicator measurements and providing their independent answer, participants could see the forecasts made by other participants, before receiving round feedback.

In the interaction phase lasting for 50 rounds, participants continued to see measurements for their respective indicator category (wind, temperature, humidity), but their forecast was now shared with other participants in their team. After seeing each other's forecasts, participants had 10 seconds to revise their initial guess and provide a final forecast for every round.

During the interaction phase, we included an algorithmic player in each team. In 15 of the 30 teams (treatment teams) this algorithmic player provided forecasts based on the VAE model we trained on the respective team's training phase data (Figure 1). In the other 15 teams (control teams), the algorithmic player provided randomly generated guesses. We compared the effect of including the VAE algorithm as an algorithmic player in a team on performance compared to a random baseline.

Stimuli The stimuli $x_{(\cdot)}$ for temperature, humidity and wind were randomly generated for all rounds of the game prior to its start. The values generated were then transformed into predictor values. The function used for this transformation was different for each predictor:

$$\text{predictor value}^{\text{hum}} = 1 + x_{\text{hum}} + 0.01\epsilon \quad (2)$$

$$\text{predictor value}^{\text{temp}} = 1 - x_{\text{temp}} + 0.01\epsilon \quad (3)$$

$$\text{predictor value}^{\text{wind}} = \begin{cases} 2, & x_{\text{wind}} \geq 2 \\ 50x_{\text{wind}}^2 - 50x_{\text{wind}} + 10 + 0.01\epsilon, & -2 < x_{\text{wind}} < 2, \\ -2, & x_{\text{wind}} \leq -2 \end{cases} \quad (4)$$

Where $\epsilon \sim N(0, 1)$ is a random noise term. These functions (ignoring the random error component) led to a positive linear relationship in the case of humidity, a negative linear relationship for temperature, and a semi-quadratic relationship for wind (see Figure S1). In other words, chances of rain were highest for (1) high humidity values; (2) low temperature values; and (3) low and high wind values.

Both stimuli and the predictor values for all 160 rounds were generated before the game started for a given team. Taking these 160 values for each predictor category as the "sample", we transformed the predictor values to z-scores. Negative z-scores had a negative effect on rain probability, while positive z-scores increase the likelihood of rain.

We then summed up the three z-scores – one for wind, temperature, and humidity each – from a given round, and transformed the resulting sum using a sigmoid function to get our rain probability for round k (see Figure S2):

$$P(\text{rain}_k = 1 | Z_k) = \frac{1}{1 + \exp(-5Z_k)} \quad (5)$$

Where $Z_k \equiv z_k^{\text{temp}} + z_k^{\text{hum}} + z_k^{\text{wind}}$ for round k .

Variational autoencoder We used our two-stage experiment to train a variational autoencoder model ("VAE" in the following) on data collected directly from participants during the first stage of the experiment ("Training phase"), and use it as an algorithmic player in the second part of the experiment ("Interaction phase"). We compared behavior in groups where the algorithmic player followed the VAE with groups where the algorithmic player provided random responses.

The VAE model was implemented using the Keras.js package and trained it on the first 110 rounds (Training phase) with a burn-in of 10 rounds to allow the players to familiarize with the task (Figure 2). An autoencoder is a type of convolutional neural network that converts a high-dimensional input into a low-dimensional one (the latent vector), and tries to reconstruct the original input with the highest quality possible from this vector. Our VAE consisted of two connected networks, one encoder and one decoder. When training the model, the encoder took as input the response matrix X collected during the training phase. Each participant in the game was treated as one feature and responses on each round were treated as different observations. The encoder returned a vector of lower dimensionality compared to the initial input features. The low dimensional space was a hidden layer with three nodes. This procedure compresses redundant information arising from response correlations among participants, akin to other dimensionality reduction techniques such as principal component analysis (PCA). The VAE differs in that (i) the encoding and decoding process is in general non-linear and (ii) the hidden nodes learn a *distribution* over latent variables and so their response is probabilistic. The architecture of the VAE requires many hyper-parameters to be set and optimised typically. In this study our aim is to prove that a VAE can perform the function of a minority supporting bot, rather than to optimise this behaviour. The latent vector was then fed to the decoder that was trained to reconstruct the original data by minimizing the difference between the input matrix X and the output matrix X' . The advantage of this technique compared to other dimensionality reduction techniques such as principal component analysis is that the latent space can be used to generate new data that has never seen by the model. In our weather forecasting task, this results in a bot that is able to

Figure 2: Schematic architecture of a variational auto-encoder. The input X is compressed by the encoder layer (green) into a hidden representational layer (red). A decoder (blue) takes as input the compressed representation and attempts to reproduce the original input as closely as possible (X'). Credit:EugenioTL, Wikipedia Commons contributor (CC BY-SA 4.0)

produce forecasts that were not made by any other human player. To train the model we used defaults parameters in the Keras.js package.

After training, we proceeded in three steps to create an algorithmic agent that could operate in the second stage ("Interaction phase"): (1) we apply K-means ($k=3$) to the last output layer's weights; (2) we create a new set of coordinates along the hidden layer (corresponding to a new set of weights) by computing the weighted average of cluster centroids obtained in 1; (3) we replace the weights of the last output layer of the VAE with this new set of weights.

1. We tested this procedure in a computer simulation using synthetic data prior to running the experiment. The code is publicly available on Open Science Framework together with the rest of the analyses accompanying this paper. We show that the last layer's weights correctly separate participants by condition. In other words, the participant distance along the hidden layer represents, after training, their similarity of responses across rounds. Figure 3 reproduce the same weights analysis with one of the teams tested. Figure 3a shows the correlation coefficients of the 10 sets of weights in the last layer of the model. High correlation coefficients represent greater weight similarity. The model learned to assign similar weights to participants giving similar responses. Similarly, figure 3b shows a 2-dimensional projection of the output weights. Each blue point corresponds to one participant in a test team. A lower distance in the projected space corresponds to a similar pattern of weights from the hidden layer to the output layer of the VAE.

2. The algorithmic participant's profile was specific for each team of participants and was defined as a new set of three coordinates along the hidden layer. The set of coordinates was obtained by averaging the clusters centroids, using weights w inversely proportional to the number of participants N in each cluster c :

$$w_c = (1/N_c)^\gamma \quad (6)$$

where γ is the parameter controlling the bias towards supporting minority views (here set to 2). Figure 3b shows a 2-d projection of the set of weight that this procedure assigned to the algorithmic participant in one of the teams recruited (orange dot). Notice that the bot has a shorter distance (*i.e.* more similar weights) from the two smaller clusters (minority opinion clusters) than to the larger cluster (majority opinion cluster).

3. After defining the algorithmic player's profile we used it to sample a new response on each subsequent round (Interaction phase). To do that, we replaced at random one output unit of the VAE (corresponding to one human player) with our new set of weights representing the algorithmic player. We then run this new VAE model on all subsequent new (human) forecasts to obtain the responses of our algorithmic player. The net effect is that the VAE bot produces an original (unseen) forecast based on the pattern of forecasts produced by other human players.

Figure 3: Example of a latent space of a variational autoencoder model trained on one of the teams in the study. (a) Correlation coefficient of the weights to the output layer of the variational autoencoder, after training. Clear structure of the data, as learned by the model, is seen in the clusters of high correlation coefficients. (b) The weights to the output layer projected on a 2-dimensional surface using principal component analysis. Three distinct clusters can be seen in the figure, each corresponding to a team of participants with similar response patterns. The model learned distinct representations corresponding to one large cluster (majority opinion) and two smaller clusters (minority opinions) as shown by the clear separation of the model’s weights in latent space. The bot player is represented in orange and shows a response pattern that is closer to the smaller clusters (minority opinions) than to the larger cluster (majority opinions).

Participants The experiment was ran double-blind on Prolific.co. We allocated incoming participants randomly between the control and treatment team, until we reached the desired 30 teams (15 control and 15 treatment).

We paid participants £8 to complete the experiment that was estimated to take 55 minutes (equivalent to £8.57/hour). On top of the flat compensation rate, participants were ranked within their group of 10 based on their score achieved during the experiment. The participant with the highest score received an additional £10 and the participant ranked second received a bonus of £5. We discuss the potential downsides of tournament incentives later in the paper.

Our participant pool is diverse compared to most laboratory experiments using student subject pools, helping us to ease some of the concerns regarding the external validity of our findings. The summary statistics of our sample demographic information is presented in the Supplementary Table S1. The mean and median age of participants is 31.8 years and 30 years, respectively (with a standard deviation of approximately 10 years). The sample is balanced with respect to gender, having 52.4% male participants.

Most participants (64.5%) reported English as their first language and the most represented nationalities with respect to the total number of participants were the UK (38.8%) and the US (21.1%). 47.8% of participants were full-time employed and students represented 30.8% of our sample.

Results

Team polarization We first tested whether the VAE bot helped reduce team polarization. Although the VAE player supported minority views more than majority views, it also represented a (weighted) average of each opinion cluster. Thus, we expected the VAE bot to bridge the gap between opinion clusters and increase alignment [30]. To test this hypothesis, we compared polarization in teams assigned to the VAE condition with polarization in control teams. We measured polarization as the standard deviation of forecasts [31], which we calculated for forecast distributions both before (*pre* SD) and after (*post* SD) exposure to peer information. Our measure of interest was Δ SD, defined as the change in the standard deviation of forecasts before and after peer exposure.

Participants saw different information according to which predictor group they were assigned to. Therefore, if one predictor suggested a high likelihood of rain while another the opposite, this would itself result in a higher standard

deviation of forecasts. To control for these spurious effects, we measure *Z Range*, which calculates the distance between the largest and smallest z-score of the three predictor values in each round:

$$ZRange_{j,k} = \max(z_{j,k}^{\text{temp}}, z_{j,k}^{\text{hum}}, z_{j,k}^{\text{wind}}) - \min(z_{j,k}^{\text{temp}}, z_{j,k}^{\text{hum}}, z_{j,k}^{\text{wind}}) \quad (7)$$

For team j and round k . We ran two mixed effects model with random effect for teams (nested within the date the game was ran on). The first model tested whether the change in polarization ΔSD was affected by our bot treatment (dummy coding: 1 = VAE bot, 0 = random bot), and controlling for z-score range. In the second model, the dependent variables was changed to post-interaction polarization (*post SD*). Results are shown in Table 1.

Post-interaction polarization also tended to be higher in VAE condition compared to the control ($\beta = .35, p = .052$). As expected, a higher *Z Range* predicted increased polarization, but did not affect the change in polarization ΔSD . We thus focused on ΔSD as this was less affected by round-by-round fluctuations in the indicators' range. The presence of VAE bots significantly increased polarization, compared to a random bot baseline ($\beta = .28, p = .01$). Overall these findings suggest that although the bot provided responses that were in between minority and majority opinions, its bias to support minority opinions more than majority opinions led to an overall increase in polarization compared to the baseline.

Dependent Variable:	<i>post SD</i>		ΔSD	
Predictors	Estimate	<i>p-value</i>	Estimate	<i>p-value</i>
(Intercept)	-0.18	0.169	-0.14'	0.086
Treatment	0.35'	0.052	0.28*	0.012
Z Range	0.11***	<0.001	-0.03	0.416
Random effects	Yes		Yes	
Observations	1500		776	
Marginal / Conditional R^2	0.043 / 0.270		0.021 / 0.073	

Table 1: Mixed Models for Team Polarization. The presence of the VAE bot in hybrid teams increased the likelihood of polarization and the spread of forecasts post social interaction.

Influence of minority opinion One hypothesis for the increased polarization observed in VAE condition was that the VAE bot, by supporting minority views, increased the influence of people holding those views against a majority. The presence of the VAE bot may have made people holding minority opinions less prone to social influence. If the minority was more influential, one would expect that final forecasts of majority groups would shift closer to the minority's initial forecasts. We thus looked at whether final forecasts of the two largest sub-groups (the 5 person majority and the 3 person mid-size condition) in teams with the VAE bot were closer to initial minority forecasts. We calculated *Minority Influence* as the absolute difference between the 2-person minority's median initial forecast and median final forecast of 3 and 5-person sub-groups separately, for each team j and round k :

$$\text{Minority Influence}_{j,k}^{\text{majority}} = 1 - |\text{med}(\text{prediction}_{I_{j,k}^{\text{minority}}}^{\text{initial}}) - \text{med}(\text{prediction}_{I_{j,k}^{\text{majority}}}^{\text{final}})| \quad (8)$$

$$\text{Minority Influence}_{j,k}^{\text{mid-size}} = 1 - |\text{med}(\text{prediction}_{I_{j,k}^{\text{minority}}}^{\text{initial}}) - \text{med}(\text{prediction}_{I_{j,k}^{\text{mid-size}}}^{\text{final}})| \quad (9)$$

Where $I_{j,k}^{\text{minority}}$, $I_{j,k}^{\text{mid-size}}$ and $I_{j,k}^{\text{majority}}$ denotes participants, who are assigned to the sub-group with a total of two, three and five participants, respectively. The variable is calculated for each team j and for each round k . A greater value indicates a greater influence of the minority cluster.

We control for round difficulty for 3 and 5-person sub-groups, as any outside sub-group influence is likely to be diminished in easy rounds (see Supporting Information for a calculation of round difficulty). We calculate *Round Difficulty* depending on which predictor category (temperature, humidity or wind) was assigned to the majority condition (N=5) and the mid-size condition (N=3). This was done to take into account the fact that, for instance, a linear relationship (e.g. temperature) was easier to learn than a quadratic one (e.g. wind).

We tested separately minority influence on the majority sub-group (5-players) and on the mid-size sub-group (3-players) by running mixed effects model with random effect for condition, nested in the date the game was ran. We regressed the treatment dummy (1 if bot is VAE, 0 if random), round difficulty and their interaction terms on *Minority Influence*.

The results in Table 2 suggests that the VAE bot reduced minority influence on the mid-sized groups in easy rounds ($\beta = -0.36, p = .03$). However, in teams with the VAE bot, minority influence on the majority increased when the majority cluster faced difficult rounds, and thus people were most uncertain ($\beta = 0.31, p < 0.001$).

Dependent Variable:	Minority Influence ^{majority}		Minority Influence ^{mid-size}	
Predictors	Estimate	p-value	Estimates	p-value
(Intercept)	0.07	0.368	0.22	0.064
Treatment	-0.14	0.181	-0.36*	0.030
Majority Difficulty	0.13*	0.014		
Treatment : Majority Difficulty	0.31***	<0.001		
Mid-Size Difficulty			0.21***	<0.001
Treatment : Mid-Size Difficulty			0.02	0.784
Random effects	Yes		Yes	
Observations	572		572	
Marginal R ² / Conditional R ²	0.101 / 0.128		0.082 / 0.219	

Table 2: Mixed Models for Minority Influence. The VAE bot was successful at increasing minority influence when the majority cluster faced difficult decisions and majority players were thus most uncertain about their responses. The VAE bot was also successful at increasing 2-person minority cluster’s influence on the mid-sized 3-person group.

Mirroring the above analysis, we also tested whether the majority was less influential in VAE teams than in control teams (the construction of majority influence variable is described in the Supporting Information) controlling for round difficulty for participants in the non-majority predictor categories. We found no main effect of treatment but once again an interaction with round difficulty. In particular, we found a reduced influence of the majority sub-group on the minority sub-group with increasing round difficulty ($\beta = -0.14, p = .03$).

Overall, these findings show that the minority group had greater influence on the majority group in VAE teams compared to control teams. On the contrary, the majority had less influence on the minority group. These effects were modulated by round difficulty as expected by the fact that people are more prone to social influence when facing difficult decisions. These findings also suggest that the presence of a VAE bot supporting minority views more than majority made the minority opinion more resistant to social influence and more influential in difficult rounds.

Dependent Variable:	Majority Influence ^{minority}		Majority Influence ^{mid-size}	
Predictors	Estimate	p-value	Estimates	p-value
(Intercept)	0.07	0.457	0.09	0.457
Treatment	-0.13	0.305	-0.23	0.191
Minority Difficulty	0.21***	<0.001		
Treatment : Minority Difficulty	-0.14*	0.036		
Mid-Size Difficulty			0.13**	0.006
Treatment : Mid-Size Difficulty			0.10	0.112
Random effects	Yes		Yes	
Observations	840		840	
Marginal R ² / Conditional R ²	0.025 / 0.116		0.047 / 0.226	

Table 3: Mixed Models for Majority Influence. The VAE bot significantly reduced the majority cluster’s influence on the 2-person minority cluster. A significant interaction between treatment and difficult was also found, suggesting that presence of the VAE bot further reduced majority cluster’s influence in difficult trials.

Individual prediction accuracy We tested whether the presence of a minority-supporting bot affected the prediction accuracy of human participants. We ran a regression model to compare changes in prediction errors after social interaction in teams with a VAE algorithmic player versus teams with a randomizing bot. We controlled for other factors affecting prediction error like round difficulty, learning success during the training phase, and quality of social information.

Prediction error was defined as the absolute value of the difference between predictions provided by individual i in round k , and the round outcome indicator (Rain=1; No Rain=0):

$$\text{prediction error}_{i,k} = |\text{prediction}_{i,k} - \text{outcome}_k| \quad (10)$$

Δerror is the change in prediction error from initial to the final forecast provided by a participant. A larger value of Δerror indicates a larger accuracy improvement. The variable is defined as:

$$\text{improvement}_{i,k} = \Delta\text{error}_{i,k} = \text{prediction error}_{i,k}^{\text{initial}} - \text{prediction error}_{i,k}^{\text{final}} \quad (11)$$

where initial and final indicate predictions made before or after seeing other team members' forecasts.

We identified three explanatory variables that could confound accuracy improvements due to our manipulation, namely (1) the accuracy of other team members' predictions in a given round (see Supplementary Information §Collective error), (2) the round's difficulty (see Supplementary Information §Round Difficulty) and (3) how well a participant had learned the relationship between predictor values and rain probability during training (see Supplementary Information §Training Error).

In addition to the above defined explanatory variables, we also control for the effect of a participant being in either the temperature, humidity, or wind predictor groups. Given that these three predictors have a different underlying relationship with rain probability, we include interaction terms between these indicator group dummy variables and the presence of a VAE bot. Including this interaction term is important, since we may expect that our treatment affects participants differently based on which predictor group they belong to. We standardized all continuous variables.

We ran a mixed regression model on Δerror (Table S6). We also report the same model run on the sign of Δerror , Δdummy , representing binary improvement (*i.e.* whether accuracy improved or not) and raw final prediction error (representing final round accuracy) - see Tables S7-S9.

The results show a positive trend ($\beta = 0.16, p = .06$) for the VAE bot condition, indicating weak accuracy improvement due to the presence of the VAE bot, and a significant interaction between treatment and wind condition ($\beta = -0.26, p = 0.03$), suggesting that the accuracy improvement was negatively affected by being assigned to a wind predictor (arguably the most difficult predictor-outcome relationship to learn). These results were also confirmed when we fitted a logistic mixed model with Δdummy as the outcome variable. Results were robust to an alternative round difficulty measure (absolute value of z-scores).

As expected, training error, collective error, and round difficulty all increased prediction error ($p < 0.001$). Furthermore, a higher collective error decreased the chance that a participant provided an improved forecast after seeing peer forecasts ($p < 0.001$) (Table S4).

To better understand what drove these accuracy improvements, we ran the same models on subsets of our sample based on which predictor group the participant belonged to. The results show that significant improvements due to VAE presence were driven by participants assigned to the humidity condition (Tables S5-S7). As the humidity condition was arguably the easiest to learn (positive linear), we interpret these results as suggesting that greater accuracy improvements were observed in those participants who were more likely to have learned the relationship of their indicator variable with the outcome. When dividing our sample based on which predictor group, we found that VAE significantly increased individual accuracy when the 2-person minority was assigned to the quadratic "wind" indicator variable (Tables S6-S7). In all other models, the only significant predictors of individual accuracy improvement were round difficulty, training error and collective error (Tables S5-S7). Overall, these findings suggest that gains on individual accuracy due to the VAE bot were small but consistent.

A caveat of this analysis is the high attrition rate observed during the initial forecast, which thus reduced the number of observations where a Δerror measure could be computed.

Team performance Further to the above models where we look at round-level observations from individual participants, we tested for differences in team accuracy between control and treatment teams. We defined team accuracy as the median team prediction error. When looking at aggregate data, we did not observe any significant difference in median error between treatment teams and median increase in prediction accuracy compared to control teams (both using a two-sample t-test ($p > .05$) and a Wilcoxon test ($p > .05$) (Figure 4).

We used two different dependent variables when testing whether our treatment had a significant effect on team performance: median team error and change in median team error. We calculated the former in a similar way as we calculated prediction error for round-level individual forecasts. We took the median prediction from a team and

Figure 4: Boxplot of Team Median Prediction Errors (top panel) and the Difference between Initial and Final Median Prediction Error (bottom panel)

286 calculated the error from this prediction. For the analysis, we are only interested in the effect of bot treatment on team
 287 accuracy exclusive of bot accuracy. For comparison, however, we report results both when predictions by bots were
 288 excluded (*median error*) and included (*median error (bot)*).

$$\text{median error}_{j,k} = |\text{med}(\text{prediction}_{j,k}^{\text{final}}) - \text{outcome}_k| \quad (12)$$

Our second variable of interest was $\Delta median error$, which measured the improvement from the median initial prediction to the median final prediction. The variable was computed for team j in round k as follows:

$$\Delta median error_{j,k} = |\text{med}(\text{prediction}_{j,k}^{\text{initial}}) - \text{outcome}_k| - |\text{med}(\text{prediction}_{j,k}^{\text{final}}) - \text{outcome}_k| \quad (13)$$

Similarly to median error, bot predictions were excluded for $\Delta median error$ and were included for $\Delta median error (bot)$.

We controlled for the same variables that were used in individual-level accuracy. Initial collective error was measured by the same variable as in the individual mixed effects models *Collective Error*, while round difficulty was simply the weighted average of the *Round Difficulty* measure used at the individual level. The weights of wind, temperature and humidity difficulty were based on the number of people in each sub-group².

To control for training success, we summed up all the prediction errors of the last 55 training rounds in a team, and then divided the sum by 550 (55 rounds $\times$ 10 participants per team):

$$\text{training error}_j = \frac{\sum_{k=56}^{110} \sum_{i=1}^{10} \text{prediction error}_{i,k}}{550} \quad (14)$$

Where $i \in I_j$ denotes participants in team j .

In addition to the above three control variables, we included interaction terms between the treatment variable and two further dummy variables indicating whether a group had two participants (the smallest possible group) in the wind condition or in the temperature condition. The models included a random effect for team, nested in the date the game took place. The full model is reported in Table S8.

The results presented in Table 4 show a marginal negative effect of our treatment on team *medianerror* ($p < .1$) for teams when temperature was assigned to the smallest minority group ($N=2$). However, this effect was not replicated with $\Delta median error$.

These findings suggest that wind minority groups in the random control condition got worse after social exposure. A trend was observed indicating that our treatment marginally reversed this effect, thus positively affecting accuracy improvements in this condition ($p = .06$). Overall, these findings suggest that improvements on team accuracy were weak and constrained by what indicator variable the 2-person minority group was assigned to. However, the VAE bot had a stronger effect in conditions when the 2-person minority cluster was assigned to the quadratic indicator ("wind").

Dependent Variable:	<i>median error</i>		<i>median error (bot)</i>		$\Delta median error$		$\Delta median error (bot)$	
Predictors	Estimate	<i>p-value</i>	Estimate	<i>p-value</i>	Estimate	<i>p-value</i>	Estimate	<i>p-value</i>
(Intercept)	-0.10	0.380	-0.10	0.332	0.12	0.212	0.09	0.319
Treatment	0.24	0.153	0.19	0.249	-0.17	0.266	-0.17	0.205
Temp. Minority	0.18	0.311	0.17	0.326	-0.26'	0.096	-0.13	0.348
Treatment : Temp. Minority	-0.49'	0.083	-0.38	0.173	0.38	0.133	0.28	0.207
Wind Minority	0.13	0.374	0.15	0.292	-0.25'	0.059	-0.12	0.287
Treatment : Wind Minority	-0.29	0.163	-0.24	0.242	0.35'	0.067	0.22	0.194
Random effects	Yes		Yes		Yes		Yes	
Observations	1500		1500		1290		1500	
Marginal / Conditional R^2	0.109 / 0.150		0.150 / 0.189		0.165 / 0.193		0.470 / 0.495	

Table 4: Mixed Model Estimates of Treatment Effect on Team Forecasts

²Sample calculation method for a team with five participants in the wind, three in humidity and two in the temperature condition: $(5 \times \text{Round Difficulty Wind} + 3 \times \text{Round Difficulty Hum} + 2 \times \text{Round Difficulty Temp})/10$.

Discussion

In this paper, we designed a strategic algorithmic player and deployed it along human players in hybrid teams performing a hidden-profile task. The bot was built on a variational-autoencoder trained to learn a low dimensional representation of opinion clusters based on the repeated observations of people judgments. The bot was programmed to generate original predictions on the fly that supported minority views more than majority views. We manipulated the size and information of three subgroups, namely a majority (5-person condition) and two minority subgroups (3 and 2-person conditions respectively) with a access to unique task-relevant information.

We expected a bot so designed could bridge the gap between opinion clusters and improve team accuracy. Instead, we found that the presence of a single minority supporting bot (representing only 10% of the team size) increased the polarization of the team, compared to a baseline condition where a control algorithmic player provided random guesses. Our original hypothesis was based on studies in social psychology, showing that people are most influenced by opinions that are in a "latitude of acceptance", *i.e.* a Goldilocks region that is not too close to their privately held opinion (which would not induce any opinion shift) and not too distant from it (which would be too distant to integrate with one's information) [4, 32]. We find evidence for an increase in the polarization of the team after the introduction of the VAE bot. This suggests that rather than bridging the gap and facilitating consensus reaching, the VAE player likely had the unintended consequence of making the minority more resilient to social influence from the majority. This result echoes some early results on persuasion and peer pressure showing that the likelihood to yield to a majority believed to be wrong dramatically decrease with each additional minority-supporting individual [1, 33]. Exposure to disagreeing opinions is rarely successful at changing one's beliefs or confidence and can sometimes have the opposite effect of entrenching people in their views even further [19, 34, 35, 36, 37]. For this reason, bots may be more effective at increasing polarization than at changing opinions [38, 39].

On the other hand, the VAE bot was unsuccessful in increasing the influence of participants in the minority conditions on the majority, suggesting that participants simply became more entrenched in their views. Yet, we also find weak but consistent evidence that the bot affected collective decision patterns in subtle ways. We found weak evidence that the VAE bot helped participants improve accuracy from their initial to final forecasts. The results in Table S6 show that this was driven by observations from temperature minority groups. These results suggest that all else being equal, minority participants assigned the temperature indicator (which had a negative linear relationship with the outcome) improved their accuracy thanks to the VAE presence more than their counterpart in the control. Our findings also show some weak evidence that the VAE bot influenced team performance, although these effects did not reach significance. The VAE bot numerically reduced final forecasting errors and error change from initial to final forecast, for specific teams (for instance in teams when the minority was assigned to a negatively linear 'temperature' indicator). However, the weak effects make interpretation of accuracy results difficult. Considering that our bot treatment represented only 10% of the entire team, these results are not surprising. Future experiments should include a larger number of strategic bots and/or stronger biases towards minority opinions [1, 33].

More importantly, our VAE algorithmic agent inferred group membership without being provided any information other than the number of clusters (k) to segment human players. However, contrary to simple clustering algorithms, the use of a variational auto-encoder made possible to sample new unseen responses from the hidden layer representing other players. This is in stark contrast with bots that simply copy human behavior. Variational auto-encoders reduce redundancy in the input in a similar way as a principal component analysis. Thus, the VAE model in our experiment likely inferred group membership by leveraging on the correlation of people forecasts over time. The model then used this learned internal representation to place itself along this hidden space so to support minority views proportionally more than majority views. This strategy was intended to maximally influence collective dynamics by facilitating consensus reaching. Although our algorithmic manipulation was not successful at reducing conflict, it did influence team dynamics, from increasing polarization to influencing individual and collective patterns of decision accuracy.

The growing accessibility of machine learning tools and large amount of data has significantly increased the sophistication of algorithmic agents online. Arguably, online platforms are more likely to block unsophisticated bots than bots that are better able to mimic human behavior and opinions. This trend might, over time, create a selection process favoring 'more human' sophisticated bots. Here, we explored how an adaptive algorithmic agents (using off-the-shelf machine learning techniques) could affect team dynamics and decision-making in a controlled environment. The consequences of smarter bots on collective dynamics is largely unknown. Understanding them will require conducting more experiments like the present work. Randomized treatments, both in the lab and in larger field experiments on real online platforms, can shed light on these complex dynamics. Even though our bot was explicitly designed to improve team performance in the hidden-profile task, the results were surprising. Our findings suggest that algorithms in hybrid teams interact in complex ways with the way that people perceive, share and integrate information to solve common goals.

Notwithstanding the novelty of the results, we must stress the fact that our analysis was exploratory in nature and many caveats exist in our paradigm. First and foremost, we observed a large rate of non-compliance when participants were asked to provide initial forecasts. This may have been driven by decision fatigue or by the fact that participants in our study were not rewarded for providing accurate initial forecasts, but only accurate final forecasts. Providing performance bonus to the top two ranked participants in a team may have reduced the incentive for team-members to contribute to a shared pool of knowledge, given that this would only making other participants more likely to achieve a higher score. Decision fatigue may also be reason why we saw few initial guesses. The experimental setting required less effort to simply look at what other participants in the team guessed before providing any forecast, compared to forecasting from the initial private information as well. In short, the attentional and cognitive cost of providing initial forecasts seem to have been greater than any associated benefit.

Finally, given the bots provided initial forecasts in each round, the lack of initial guesses from human participants may have artificially increased the influence of bot forecasts on our findings. This may result in an inflated effect size compared to a scenario where all participants provide initial forecasts. Although far from perfect, we wish that our methodology can stimulate more experimental work to understand these phenomena. As seen in this work, subtle and unexpected effects may come from using off-the-shelf machine learning algorithms in hybrid social systems.

Conclusions

The increase in sophistication of social bots and the availability of off-the-shelf machine learning algorithms is likely to create a generation of smart algorithmic agents able to map opinion clusters and actively infer group membership. Generative models such as variational auto-encoders and generative adversarial networks can be used to produce bots that can strategically position themselves along arbitrary opinion spaces to maximally influence collective dynamics. In this paper, we explored how a single algorithmic agent – implemented using readily available machine learning tools– can be used to solve the hidden-profile task by strategically supporting minority views against a dominant majority.

Pre-registration materials

Pre-registered hypotheses are publicly available on the Open Science Framework: <https://doi.org/10.17605/OSF.IO/KF367>

Replicability

Code and data to reproduce figures and analysis is available via the Open Science Framework: Pescetelli, N., Reichert, P., & Rutherford, A. (2021, October 13). A variational-autoencoder approach to solve the hidden profile task in hybrid human-machine teams. Retrieved from osf.io/t38z9

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489 **Supplementary Figures**

Figure S1: Predictor functions on the $[0, 1]$ interval (pink horizontal line represents the function average on this interval)

Figure S2: Sigmoid Function Calculating Rain Probability

Figure S3: Prediction Error by Algorithmic players: Random bots vs. VAE (separated by which predictor group was in the minority)

Figure S4: Histogram of Predictions: Random vs. VAE

VAE Bot versus Random Forecasts

As a start of our analysis, we want to understand how the VAE model performs versus randomly generated guesses. Figure S3 shows that VAE bots provide lower prediction error than randomized answers, with the 95% confidence intervals of the median not overlapping for bots trained in humidity and wind groups. The boxplots show that VAE with humidity predictor group as the minority performs the best, while wind and temperature perform approximately the same.

To test formally if the trained model has better accuracy compared to random predictions, we run a simple OLS estimation where we regress the treatment dummy (“VAE”, 1 if prediction was provided by the VAE algorithm, 0 if it was provided by the randomizing bot), average round difficulty, and dummies for wind and humidity minority on prediction error. The significant ($p < 0.001$) negative coefficient on the treatment dummy indicates that the VAE model provides forecasts with lower prediction error (see Table S2 for results), representing an improvement of 11.5%.

We can observe that the trained model’s predictions are closer to a bell-shaped distribution with a positive skew, while the randomized predictions are more skewed towards the extremes (see Figure S4).

Round Difficulty

The predictor functions include a random noise term, which we ignore for the below calculations. As the z-score of predictor values determines if it has a negative (negative z-score) or positive (positive z-score) effect on rain probability, we just need to find the predictor value that corresponds to the predictor function’s average on the $[0, 1]$ interval. Humidity and temperature have a linear positive, and linear negative relationship with rain probability, respectively. The linear relationship makes it straight-forward to calculate which predictor value provides the least amount of information to participants. The average of an either decreasing or increasing linear function on the 0,1 interval is at $x = 0.5$, which is our most ambiguous stimuli value for both humidity and temperature predictors. As wind has a quadratic relationship with rain probability, we will have not one, but two “most ambiguous” values, denoted by x_1 and x_2 .

The wind predictor function is given by $f(x) = 50x^2 - 50x + 10 + \epsilon$, where $x \in [0, 1]$ and $\epsilon \sim N(0, 1)$, but $f(x) = 2$ if $x \leq -2$ and $0.8 \leq x \leq 1$, furthermore, $f(x) = -2$ if $x \leq -2$. The alternative representation of this function (setting aside the random noise term) is:

$$f(x) = \begin{cases} 2, & 0 \leq x < 0.2 \\ 50x^2 - 50x + 10, & 0.2 \leq x < 0.4 \\ -2, & 0.4 \leq x < 0.6 \\ 50x^2 - 50x + 10, & 0.6 \leq x < 0.8 \\ 2, & 0.8 \leq x \leq 1 \end{cases} \quad (15)$$

When calculating the function average for $f(x)$ on interval $[a, b]$, we use the following well-known formula:

$$\bar{f}_{a,b} = \frac{1}{b-a} \int_a^b f(x) dx \quad (16)$$

Following the above calculations, we obtain $x_1 = 0.264755$ and $x_2 = 0.735245$. After we calculated the most ambiguous stimuli for all three predictor categories, we then measure round difficulty by the relative distance of the stimuli from the most ambiguous stimulus or stimuli (note that the calculation of wind difficulty depends on which interval the wind stimuli belongs to):

$$\text{Round Difficulty}_{i,k} = \begin{cases} 1 - |0.5 - \text{hum}_k|/0.5, & \text{predictor group}_i = \text{humidity} \\ 1 - |0.5 - \text{temp}_k|/0.5, & \text{predictor group}_i = \text{temperature} \\ \text{Wind Difficulty}_k, & \text{predictor group}_i = \text{wind} \end{cases} \quad (17)$$

Where Wind Difficulty is calculated as:

$$\text{Wind Difficulty}_k = \begin{cases} 1 - [(x_1 - \text{wind}_k)/x_1], & \text{wind}_k < x_1 \\ 1 - [(0.5 - \text{wind}_k)/(0.5 - x_1)], & x_1 \leq \text{wind}_k < 0.5 \\ 1 - [(x_2 - \text{wind}_k)/(x_2 - 0.5)], & 0.5 \leq \text{wind}_k < x_2 \\ 1 - [(\text{wind}_k - x_2)/(1 - x_2)], & x_2 \leq \text{wind}_k \end{cases} \quad (18)$$

Essentially, we measure the percentage deviation from the most “ambiguous points” of each predictor value (humidity, temperature, wind) in a round. By subtracting the resulting value from 1, we have a higher value of Round Difficulty_{*i,k*} indicating a more difficult round for participant *i*.

3 Majority Influence

Our approach to constructing majority influence is very similar to what we used to calculate minority influence. We calculated the absolute difference between the median of the initial majority forecasts and the median final forecast for the other two sub-group sizes (2-person minority or 3-person mid-size sub-group):

$$\text{Majority Influence}_{j,k}^{\text{majority}} = 1 - |\text{med}(\text{prediction}_{I_{j,k}^{\text{majority}}}^{\text{initial}}) - \text{med}(\text{prediction}_{I_{j,k}^{\text{minority}}}^{\text{final}})| \quad (19)$$

$$\text{Majority Influence}_{j,k}^{\text{mid-size}} = 1 - |\text{med}(\text{prediction}_{I_{j,k}^{\text{majority}}}^{\text{initial}}) - \text{med}(\text{prediction}_{I_{j,k}^{\text{mid-size}}}^{\text{final}})| \quad (20)$$

4 Collective Error

Collective error was defined as the prediction error measured from the team median prediction excluding the participant’s own prediction. The collective error for participant *i* of team *j* in round *k* is defined as:

$$\text{Collective Error}_{i,j,k} = |\text{med}(\text{prediction}_{I_{j,k}^{-i}}^{\text{initial}}) - \text{outcome}_k| \quad (21)$$

Where the I_j^{-i} subscript indicates the participants in team *j* excluding participant *i*.

5 Training Error

In the accuracy regression models in the main text, we control for how well a participant learned the relationship between their assigned predictor and the outcome. We were interested in the participant’s final learning at the end of the training phase. Therefore, we constructed training error as the average prediction error in the last half of the training phase, which corresponds to 55 rounds³:

$$\text{training error}_i = \frac{\sum_{k=56}^{110} \text{prediction error}_{i,k}}{55} \quad (22)$$

³We ignore rounds where no forecast was provided by a participant (we remove these observations from both the numerator and the denominator in the equation).

537 **Supplementary tables**

Table S1: Summary Statistics of Sample Demographics

	N	Mean	SD	Median	Min	Max
Age	295	31.837	10.083	30	18	66
Gender	292	0.524	0.500	1	0	1
n. of Submissions	299	178.930	189.366	114	1	1149
Approval Ratio	299	0.990	0.033	1	0.6	1
First Language	Percentage	Nationality	Percentage			
English	64.5	United Kingdom	38.8			
Other	22.1	Other	28.1			
Portuguese	7.0	United States	21.1			
Polish	6.4	Poland	6.4			
		Portugal	5.7			
Employment Status	Percentage	Student Status	Percentage			
Full-Time	47.8	No	66.6			
Other	23.4	Yes	30.8			
Part-Time	16.4	Other	2.7			
Unemployed (and job seeking)	12.4					

Table S2: Prediction Error by Algorithmic Players: Random vs. VAE (OLS regression)

Predictors	Prediction Error		
	Estimates	CI	<i>p-value</i>
(Intercept)	0.52***	0.47 – 0.58	<0.001
VAE	-0.06***	-0.08 – -0.03	<0.001
Avg. Difficulty	0.03	-0.05 – 0.11	0.495
Wind Minority	-0.03	-0.07 – 0.01	0.138
Humidity Minority	-0.06**	-0.11 – -0.02	0.003
Observations	1500		
R^2 / R^2 adjusted	0.016 / 0.014		

Table S3: Summary of Mixed Model Estimates of Treatment Effect on full sample (full results including all predictors are reported in Tables S4-S7)

Dependent Variable:	<i>prediction error</i>		Δ error		Δ dummy	
Predictors	Estimate	<i>p-value</i>	Estimate	<i>p-value</i>	Odds Ratio	<i>p-value</i>
(Intercept)	0.02	0.546	-0.09	0.129	0.98	0.866
Treatment	0.00	0.982	0.16'	0.068	1.41'	0.081
Temperature	-0.00	0.977	0.11	0.206	1.48*	0.034
Treatment : Temperature	0.00	0.95	-0.14	0.235	0.78	0.332
Wind	-0.06	0.142	0.15'	0.08	1.52*	0.026
Treatment : Wind	0.00	0.928	-0.26*	0.033	0.64'	0.094
Random effects	Yes		Yes		Yes	
Logistic Mixed Model	No		No		Yes	
Observations	14522		2536		2536	
Marginal / Conditional R ²	0.039 / 0.172		0.027 / 0.148		0.045 / 0.179	

Table S4: DV: prediction error, Δ error, Δ dumny

Dependent Variable: Predictors	prediction error		Δ error		Δ dumny	
	Estimates	CI	p-value	Estimates	CI	p-value
(Intercept)	0.02	-0.04 – 0.08	0.546	-0.09	-0.22 – 0.03	0.129
Treatment	0.00	-0.08 – 0.08	0.982	0.16'	-0.01 – 0.33	0.068
Temperature	-0.00	-0.08 – 0.07	0.977	0.11	-0.06 – 0.27	0.206
Wind	-0.06	-0.14 – 0.02	0.142	0.15'	-0.02 – 0.32	0.08
Round Difficulty	0.11***	0.09 – 0.13	<0.001	-0.04'	-0.08 – 0.00	0.057
Collective Error	0.06***	0.03 – 0.08	<0.001	-0.15***	-0.19 – -0.11	<0.001
Training Error	0.15***	0.13 – 0.17	<0.001	0.02	-0.03 – 0.07	0.525
Treatment x Temperature	0.00	-0.10 – 0.10	0.95	-0.14	-0.36 – 0.09	0.235
Treatment x Wind	0.00	-0.10 – 0.11	0.928	-0.26*	-0.50 – -0.02	0.033
Random Effects						
σ^2	0.82			0.86		3.29
τ_{00}	0.12 _{roundId}			0.10 _{roundId}		0.44 _{roundId}
ICC	0.02 _{prolIficId;gameId:date}			0.03 _{prolIficId;gameId:date}		0.09 _{prolIficId;gameId:date}
N	0.14			0.12		0.14
	293 _{prolIficId}			244 _{prolIficId}		244 _{prolIficId}
	30 _{gameId}			30 _{gameId}		30 _{gameId}
	7 _{date}			7 _{date}		7 _{date}
	1500 _{roundId}			1290 _{roundId}		1290 _{roundId}
Observations	14522			2536		2536
Marginal R2 / Conditional R2	0.039 / 0.172			0.027 / 0.148		0.045 / 0.179

Table S5: DV: prediction error

Sample Dependent Variable:	Full prediction error			Temperature Subset prediction error			Humidity Subset prediction error			Wind Subset prediction error			
Predictors	Estimates	CI	p-value	Estimates	CI	p-value	Estimates	CI	p-value	Estimates	CI	p-value	
(Intercept)	0.02	-0.04 – 0.08	0.546	0.02	-0.04 – 0.09	0.477	0.01	-0.05 – 0.08	0.74	-0.04	-0.10 – 0.02	0.155	
Treatment	0.00	-0.08 – 0.08	0.982	0.00	-0.09 – 0.09	0.988	0.01	-0.08 – 0.10	0.868	0.01	-0.08 – 0.09	0.879	
Round	Diffi-	0.11***	0.09 – 0.13	<0.001	0.11***	0.07 – 0.14	<0.001	0.17***	0.13 – 0.20	<0.001	0.05**	0.02 – 0.09	0.002
culty													
Collective Er-	0.06***	0.03 – 0.08	<0.001	0.02	-0.01 – 0.06	0.154	0.12***	0.08 – 0.15	<0.001	0.06***	0.03 – 0.09	<0.001	
ror													
Training Error	0.15***	0.13 – 0.17	<0.001	0.12***	0.08 – 0.16	<0.001	0.11***	0.07 – 0.15	<0.001	0.21***	0.17 – 0.24	<0.001	
Temperature	-0.00	-0.08 – 0.07	0.977										
Wind	-0.06	-0.14 – 0.02	0.142										
Treatment x	0.00	-0.10 – 0.10	0.95										
Temperature													
Treatment x	0.00	-0.10 – 0.11	0.928										
Wind													
Random Effects													
σ^2	0.82			0.75			0.49			0.72			
τ_{00}	0.12 _{roundId}			0.26 _{roundId}			0.40 _{roundId}			0.17 _{roundId}			
ICC	0.02 _{prolificId:gameId:date}			0.02 _{prolificId:gameId:date}			0.01 _{prolificId:gameId:date}			0.01 _{prolificId:gameId:date}			
N	0.14			0.27			0.46			0.2			
	293 _{prolificId}			111 _{prolificId}			98 _{prolificId}			84 _{prolificId}			
	30 _{gameId}			30 _{gameId}			30 _{gameId}			30 _{gameId}			
	7 _{date}			7 _{date}			7 _{date}			7 _{date}			
	1500 _{roundId}			1500 _{roundId}			1500 _{roundId}			1500 _{roundId}			
Observations	14522			5512			4826			4184			
Marginal R2	0.039 / 0.172			0.024 / 0.287			0.055 / 0.486			0.065 / 0.255			
/ Conditional R2													

Table S6: DV: Δ error

Sample Dependent Variable:	Full Δ error	Temperature Subset Δ error			Humidity Subset Δ error			Wind Subset Δ error		
Predictors (Intercept)	Estimates	CI	p-value	Estimates	CI	p-value	Estimates	CI	p-value	
Treatment	0.16*	-0.22 – 0.03	0.129	0.01	-0.13 – 0.15	0.882	-0.10	-0.22 – 0.02	0.116	
Round Dif-	-0.04*	-0.01 – 0.33	0.068	0.02	-0.17 – 0.21	0.831	0.19*	0.02 – 0.37	0.03	
ficuly		-0.08 – 0.00	0.057	-0.10**	-0.17 – -0.03	0.006	-0.01	-0.08 – 0.07	0.823	
Collective	-0.15***	-0.19 – -0.11	<0.001	-0.19***	-0.26 – -0.12	<0.001	-0.06	-0.13 – 0.02	0.145	
Error									-0.14***	
Training Er-	0.02	-0.03 – 0.07	0.525	0.03	-0.08 – 0.14	0.581	0.05	-0.05 – 0.15	0.323	
ror									-0.00	
Temperature	0.11	-0.06 – 0.27	0.206							
Wind	0.15*	-0.02 – 0.32	0.08							
Treatment	-0.14	-0.36 – 0.09	0.235							
x Tempera-										
ture										
Treatment x	-0.26*	-0.50 – -0.02	0.033							
Wind										
Random Ef-										
fects										
σ^2	0.86			0.94			0.6		0.87	
τ_{00}	0.10 _{roundId}			0.13 _{roundId}			0.32 _{roundId}		0.01 _{roundId}	
ICC	0.03 _{proli ficId:gameId:date}			0.06 _{proli ficId:gameId:date}			0.02 _{proli ficId:gameId:date}		0.00 _{proli ficId:gameId:date}	
N	0.12			0.16			0.36			
	244 _{proli ficId}			87 _{proli ficId}			82 _{proli ficId}		75 _{proli ficId}	
	30 _{gameId}			29 _{gameId}			30 _{gameId}		30 _{gameId}	
	7 _{date}			7 _{date}			7 _{date}		7 _{date}	
	1290 _{roundId}			756 _{roundId}			582 _{roundId}		719 _{roundId}	
Observations	2536			972			727		837	
Marginal	0.027 / 0.148			0.038 / 0.195			0.015 / 0.372		0.025 / NA	
R2 / Con-										
ditional										
R2										

Table S7: DV: Δ dumny

Sample Dependent Variable:	Full Δ dumny	Temperature Subset Δ dumny			Humidity Subset Δ dumny			Wind Subset Δ dumny		
		CI	<i>p-value</i>	Odds Ratios	CI	<i>p-value</i>	Odds Ratios	CI	<i>p-value</i>	
Predictor:										
(Intercept)	0.98	0.75 – 1.28	0.866	1.35*	1.02 – 1.79	0.038	0.94	0.72 – 1.24	0.673	1.42**
Treatment	1.41'	0.96 – 2.06	0.081	1.14	0.78 – 1.66	0.505	1.44'	0.98 – 2.12	0.067	0.93
Round	0.96	0.88 – 1.05	0.413	0.89	0.77 – 1.03	0.111	1.02	0.87 – 1.19	0.829	0.99
Diff-										
culty										
Collective	0.68***	0.61 – 0.75	<0.001	0.64***	0.55 – 0.74	<0.001	0.81*	0.68 – 0.96	0.014	0.71***
Error										
Training	0.93	0.84 – 1.04	0.228	1.03	0.83 – 1.28	0.766	0.92	0.73 – 1.17	0.498	0.90
Error										
Temperature	1.48*	1.03 – 2.13	0.034							
Wind	1.52*	1.05 – 2.19	0.026							
Treatment	0.78	0.47 – 1.29	0.332							
x Tem-										
pera-										
ture										
Treatment	0.64'	0.38 – 1.08	0.094							
x Wind										
Random										
Effects										
σ^2	3.29			3.29			3.29			3.29
τ_{00}	0.44 _{roundId}			0.13 _{roundId}			0.23 _{roundId}			0.03 _{roundId}
ICC	0.09 _{prolificId:gameId:date}			0.18 _{prolificId:gameId:date}			0.12 _{prolificId:gameId:date}			0.01 _{prolificId:gameId:date}
N	0.14			0.09			0.1			0.01
	244 _{prolificId}			87 _{prolificId}			82 _{prolificId}			75 _{prolificId}
	30 _{gameId}			29 _{gameId}			30 _{gameId}			30 _{gameId}
	7 _{date}			7 _{date}			7 _{date}			7 _{date}
	1290 _{roundId}			756 _{roundId}			582 _{roundId}			719 _{roundId}
Observa	2536			972			727			837
Marginal	0.045 / 0.179			0.057 / 0.138			0.025 / 0.119			0.038 / 0.049
R2 /										
Condi-										
tional										
R2										

Table S8: DV: median error, median error (bot), Δ median error, Δ median error (bot)

Dependent Variable:	median error			median error (bot)			Δ median error			Δ median error (bot)		
	Est.	CI	p-value	Est.	CI	p-value	Est.	CI	p-value	Est.	CI	p-value
Predictors												
(Intercept)	-0.10	-0.31 - 0.12	0.380	-0.10	-0.31 - 0.11	0.332	0.12	-0.07 - 0.32	0.212	0.09	-0.08 - 0.26	0.319
Treatment	0.24	-0.09 - 0.56	0.153	0.19	-0.13 - 0.51	0.249	-0.17	-0.46 - 0.13	0.266	-0.17	-0.42 - 0.09	0.205
Temp. Minority	0.18	-0.17 - 0.53	0.311	0.17	-0.17 - 0.51	0.326	-0.26	-0.57 - 0.05	0.096	-0.13	-0.41 - 0.14	0.348
Wind Minority	0.13	-0.16 - 0.41	0.374	0.15	-0.13 - 0.43	0.293	-0.25	-0.50 - 0.01	0.059	-0.12	-0.35 - 0.10	0.288
Round Difficulty	0.20	0.15 - 0.25	<0.001	0.18	0.14 - 0.23	<0.001	-0.14	-0.19 - -0.09	<0.001	-0.13	-0.17 - -0.10	<0.001
Training Error	0.13	0.03 - 0.23	0.012	0.11	0.01 - 0.21	0.026	-0.10	-0.19 - -0.01	0.033	-0.08	-0.16 - -0.01	0.035
Collective Error	0.20	0.15 - 0.24	<0.001	0.31	0.26 - 0.35	<0.001	0.41	0.35 - 0.46	<0.001	0.68	0.64 - 0.71	<0.001
Treatment x Temp. Minority	-0.49	-1.05 - 0.06	0.083	-0.38	-0.93 - 0.17	0.173	0.38	-0.12 - 0.88	0.133	0.28	-0.16 - 0.72	0.207
Treatment x Wind Minority	-0.29	-0.71 - 0.12	0.163	-0.24	-0.65 - 0.16	0.242	0.35	-0.02 - 0.72	0.067	0.22	-0.11 - 0.54	0.194
Random Effects												
σ^2	0.86			0.82			0.82			0.51		
τ_{00}	0.04	$gameId:date$		0.04	$gameId:date$		0.03	$gameId:date$		0.03	$gameId:date$	
ICC	0.05			0.05			0.03			0.05		
N	30	$gameId$		30	$gameId$		30	$gameId$		30	$gameId$	
	τ_{date}			τ_{date}			τ_{date}			τ_{date}		
Observations	1500			1500			1290			1500		
Marginal R2 / Conditional R2	0.109 / 0.150			0.150 / 0.189			0.165 / 0.193			0.470 / 0.495		

Table S9: Logit Mixed Model (DV: Δ dummy) Estimates of Treatment Effect on Sample Subsets (w.r.t. minority). "O.R." stands for "Odds Ratios".

Sample Dependent Variable: Predictors	Full				Temperature Min.				Humidity Min.				Wind min.			
	O.R.	Δ dummy CI	p-value	O.R.	O.R.	CI	p-value	O.R.	O.R.	CI	p-value	O.R.	O.R.	CI	p-value	O.R.
(Intercept)	0.98	0.75 – 1.28	0.866	0.92	0.52 – 1.63	0.776	0.90	0.48 – 1.67	0.734	1.02	0.72 – 1.45	0.895				
Treatment	1.41	0.96 – 2.06	0.081	2.63	1.15 – 6.00	0.022	1.70	0.63 – 4.61	0.294	1.12	0.69 – 1.82	0.637				
Temperature	1.48	1.03 – 2.13	0.034	2.19	0.82 – 5.89	0.119	1.51	0.74 – 3.07	0.255	1.29	0.78 – 2.14	0.326				
Wind	1.52	1.05 – 2.19	0.026	1.88	0.86 – 4.09	0.112	1.69	0.80 – 3.56	0.170	1.33	0.79 – 2.26	0.286				
Round Difficulty	0.96	0.88 – 1.05	0.413	0.97	0.79 – 1.19	0.762	0.91	0.77 – 1.07	0.242	1.00	0.88 – 1.14	0.962				
Training Error	0.93	0.84 – 1.04	0.228	0.92	0.64 – 1.30	0.626	0.98	0.78 – 1.22	0.823	0.92	0.80 – 1.07	0.298				
Collective Error	0.68	0.61 – 0.75	<0.001	0.57	0.45 – 0.73	<0.001	0.62	0.52 – 0.75	<0.001	0.75	0.66 – 0.87	<0.001				
Treatment x Temperature	0.78	0.47 – 1.29	0.332	0.29	0.09 – 0.95	0.041	0.59	0.19 – 1.82	0.357	1.18	0.60 – 2.32	0.623				
Treatment x Wind	0.64	0.38 – 1.08	0.094	0.25	0.08 – 0.77	0.016	0.43	0.14 – 1.34	0.147	1.04	0.50 – 2.16	0.909				
Random Effects																
σ^2	3.29			3.29			3.29					3.29				
τ_{00}	0.44 _{roundId}			0.26 _{roundId}			0.33 _{roundId}					0.60 _{roundId}				
ICC	0.09 _{prolific_id:gameID:date}			0.05 _{prolific_id:gameID:date}			0.05 _{prolific_id:gameID:date}					0.08 _{prolific_id:gameID:date}				
N	0.14			0.09			0.10					0.17				
	244 _{prolific_id}			41 _{prolific_id}			72 _{prolific_id}					131 _{prolific_id}				
	30 _{gameId}			5 _{gameId}			9 _{gameId}					16 _{gameId}				
	7 _{date}			5 _{date}			5 _{date}					7 _{date}				
	1290 _{roundId}			224 _{roundId}			372 _{roundId}					694 _{roundId}				
Observations	2536			466			747					1323				
Marginal R2 / Conditional R2	0.045 / 0.179			0.105 / 0.182			0.069 / 0.166					0.030 / 0.196				