Subjective probability is modulated by emotions

Lara Bertram[1,2,3,*], **Eric Schulz**[3], **and Jonathan D. Nelson**[1,2]

[1]University of Surrey, School of Psychology, Guildford, GU2 7XH, United Kingdom
[2]Max Planck Institute for Human Development, MPRG Information Search, Ecological and Active Learning Research with Children, Berlin, 14195, Germany
[3]Max Planck Institute for Biological Cybernetics, MPRG Computational Principles of Intelligence, Tübingen, 72076, Germany
[4]Cambridge Judge Business School, University of Cambridge, Trumpington Street, Cambridge CB2 1AG, United Kingdom
[*]lara.bertram@surrey.ac.uk

ABSTRACT

Information about risks and probabilities is ubiquitous in our environment, forming the basis for decisions in an uncertain world. Emotions are known to modulate subjective probability assessments when probabilistic information is emotionally valenced. Yet little is known about the role of emotions in subjective probability assessment of affectively neutral events. We investigated this in one correlational study (Study 1, *N* = 162) and one experimental study (Study 2, *N* = 119). As predicted, we found that emotional dominance modulated the degree of conservatism in respondents' neutral probability estimates. Remarkably, this pattern also transferred to realistic risk assessments. Furthermore, respondents' tendency to use the representativeness heuristic as a proxy for probability was increased in high dominance individuals. Our findings highlight the importance of considering emotions, particularly the little-understood emotion dimension dominance, in research on probabilistic cognition.

Introduction

Choices in financial investments, health, and even personal relationships require making decisions based on probabilistic information. Thus, a great deal of research has investigated how people estimate probabilities. The finding that people do not strictly follow the axioms of probability theory when assessing probabilities was first seen in early work in the intuitive statistician framework[1,2], and became famous with research on heuristics and biases[3,4] and fast-and-frugal heuristics[5,6].

Of key relevance here are compound events, also known as conjunctive events. Compound events are probabilistic events comprised of a series of elementary events, each of which has a particular probability. The probability of a compound event is mathematically derived by multiplying the probabilities of each of its elementary events. Instead of following this multiplicative approach, people generally tend to overestimate the probability of compound events[7–9].

When assessing the relative probability of compound events, people may also use the representativeness heuristic[10,11], basing their probability estimate on the similarity between a sample consisting of multiple elementary events and its generating distribution. Imagine you buy one ticket for a weekly lottery five weeks in a row. Each time you play, the odds of winning are 1 in 5, i.e., $p(win) = 0.2$ and $p(lose) = 0.8$. Consider two possible compound events: the representative event entails losing in each of the first four weeks, and then winning in week five; the nonrepresentative event entails losing five weeks in a row. Which compound event is more likely? Mathematically speaking, the probability of the representative compound event ($0.8^4 \cdot 0.2 \approx 0.08$) is much lower than the probability of the non-representative event

$(0.8^5 \approx 0.33)$. However, a person basing their judgments on representativeness would mistakenly select the more representative compound event as more probable.

Another reliable deviation from probability theory when assessing compound probabilities is conservatism[2]. In the revision-of-opinion literature, conservatism describes the finding that people put too much weight on prior probabilities or background information, as opposed to likelihoods or individuating information, when estimating probabilities based on sequential sampling and belief updating[2]. In the context of single probability estimates, conservatism describes the tendency to avoid extreme probability estimates, especially if the true probabilities are close to zero[12,13]. This results in more similar probability estimates for high and low likelihood compound events than is mathematically correct.

A number of models have been proposed to explain conservatism in single probability estimates. Within a Bayesian framework, as in the Bayesian Sampler Model[14], probability estimates can be seen as the result of a sampling process from memory with Bayesian updating using a generic prior. This prior can be thought of as a person's initial beliefs, which are updated in the light of incoming evidence. Differences in people's priors affect the degree of conservatism in their compound probability estimates: the stronger the prior, the more people avoid the extremes, because incoming information has a smaller impact on the posterior probability in the updating process. Another way to explain conservatism is by assuming noise in human information processing, resulting in a regression of probability estimates towards a mean of 0.5[13]. This idea is also at the heart of the Probability Theory Plus Noise model (PT+N)[15] which conceptualizes probabilistic cognition as fundamentally based on the axioms of probability theory. Deviations, such as conservatism, are explained by noise which is added to the representation of probabilistic information.

Considerations about the basic cognitive building blocks and processes underlying subjective probability raise questions about inter- and intraindividual variability in probabilistic cognition. For example, what makes people's probability assessments more or less conservative? Which psychological factors increase a person's tendency to process information in a heuristic way?

One sensible place to look would be in emotions, which are a key source of inter- and intraindividual variability in cognition and behavior[16–33]. What is known about the role of emotions in probabilistic cognition? Research has focused on information environments where probabilistic information was associated with positive or negative outcomes[22–26]. For these affectively valenced stimuli, positive emotions have been found to foster optimistic assessment, i.e., increased estimates for desired outcomes and decreased estimates for undesired outcomes, and negative emotions to foster pessimistic assessments, i.e., decreased estimates for desired and increased estimates for undesired outcomes[22,30]. Positive emotions have also been found to promote heuristic information processing, whereas negative emotions promote systematic processing of information[27–29]. One interpretation is that a positive emotion signals a safe environment and no need to engage in costly information processing, whereas a negative emotion signals a threat or a problem that requires a systematic analysis of the situation. These results support the view of an ecologically adaptive function of emotions as indicating to a decision maker when a risky decision is appropriate and when it is not[31,32].

Another well-studied emotion dimension is arousal: high arousal predicts choices for a safe over an unsafe option in situations characterized by high risk and a low likelihood of the desired outcome[23]. Arousal also shapes information processing on a fundamental level: From research on the relationship between emotional arousal and cognitive processes, we know that medium and moderately increased levels of arousal narrow the focus of attention, allowing people to focus on the most important information only and to use simpler decision strategies[25]. The Yerkes-Dodson law[34–36] describes an inverse U-shaped relationship between arousal and cognitive performance. It has even been demonstrated on a neural level[37] that intermediate activation is optimal for stimulus detection.

But emotions do not differ only in their valence and arousal. Cognitive emotion theories explain emotion-specific cognition as the result of activation patterns on several appraisal dimensions, such as uncertainty and control[17–21]. These in turn modulate the perception and evaluation of the environment. For instance, fear and anger, which are both negatively-valenced and characterized by increased arousal, are associated with very different appraisal patterns. Fear is characterized by high uncertainty and low control, and fosters systematic processing and pessimistic risk assessments. Anger is characterized by low uncertainty and high control, and fosters heuristic processing and optimistic risk assessments[18,26].

Despite this rich theoretical framework for considering emotion and cognition, little is known about the role of emotions in estimating probabilities of affectively neutral events. Given evidence that emotions interact with cognitive processes on a fundamental level, this gap in the literature is remarkable. Our research sheds light on the little-understood interplay between emotions and estimates of neutral compound probabilities. Our aim was to identify the characteristics of emotions that shape probabilistic cognition in neutral environments.

Whereas previous research on emotion-dependent cognition has often focused on the emotion dimensions valence and arousal[27,28,38], we were particularly interested in emotional dominance[39,40]. The emotion dimension dominance is characterized by a person's perceived level of control, influence, autonomy and importance. Emotional dominance also reflects the subjective level of confidence a person has in her own judgments[41,42]. Emotional dominance is also associated with unique patterns of neural activation[43] and consumer behavior[44]. We predicted that emotional dominance would foster heuristic information processing and conservatism in probability estimates.

According to cognitive emotion theories, appraisals of certainty and control modulate information processing[18] and risk assessments[26], with high control and low uncertainty fostering heuristic information processing. We expected emotional dominance to play a corresponding role in information processing, risk and probability assessments. Further support for our predictions comes from the finding that emotional dominance is positively associated with emotional valence[45]. Positive valence fosters heuristic information processing, whereas negative valence increases systematic information processing and pessimistic risk assessments. Given the shared variance between emotional dominance and valence[39], we would expect these emotion dimensions to exert a similar influence on cognitive processes. Importantly, however, emotional dominance explains variance in emotional experiences that valence cannot account for. For example, anger and anxiety – both negatively valenced emotions – can be distinguished by their emotional dominance (anger is characterized by high dominance and anxiety by low dominance). The fact that these emotions can also be distinguished by appraisals of certainty and control supports the interpretation of dominance as a link between valence- and appraisal-centered emotion theories.

Another way to consider the role of emotional dominance in cognition is by zooming in on the functional importance of emotional experiences for an organism. A useful theoretical framework for conceptualizing emotion-cognition interactions is adaptive rationality[31], with emotions seen as a source of adaptivity in cognition and behavior[32,33]. Emotions signal to an organism how beneficial the investment of mental resources is, modulating the cost-benefit ratio of cognitive effort. A person high in emotional dominance might see the world as relatively stable due to her high subjective control and confidence. The necessity to search for information and process this information systematically may be perceived as relatively low if emotional dominance is high and incoming information may alter that person's model of the world relatively little. In Bayesian terms, a person high in emotional dominance may sample less information than a person low in dominance and this person may use a strong prior when updating her beliefs based on sampled information. This would in turn result in larger deviations from the axioms of probability[14], and increase conservatism.

Summing up, we see emotional dominance as the conceptual link between cognitive and valence-based accounts of emotion-cognition interactions. Based on existing evidence on the role of emotional valence and cognitive appraisals of certainty and control in cognitive processes, we hypothesized that individuals high in emotional dominance would evaluate probabilistic information in a more heuristic way than individuals low in dominance. Assuming a functional role of emotional dominance for the cost-benefit calculation of cognitive effort, we expected high-dominance individuals to be more conservative in their compound probability estimates, putting more weight on the prior relative to likelihoods, in the probability estimation process.

Study 1 was conducted at the onset (March-April 2020) of the COVID-19 pandemic. In this preregistered study, we investigated the correlational associations between the emotion dimensions valence, dominance and arousal, and participants' probability estimates. We hypothesized that people would experience elevated levels of negative emotions and decreased emotional dominance, high uncertainty and low control at the onset of the pandemic. We were interested in the modulating role of these naturally occurring emotions in people's probability estimates. Thus, we asked participants in two tasks (Fig. 1 c, d) to estimate the probability of a series of compound events varying in mathematical probability that were generated from a known probability distribution. For this, participants were first presented with an ordered icon array of the probability distribution. Then, an example of a mixed distribution was shown and respondents were told that a three-item compound event would be sampled from that distribution with replacement. Participants were asked to first select the most probable compound event and then rate the probability of all compound events in percent using a slider. The underlying probability distributions and queried compound events differed between tasks. We assessed emotional dominance, valence and arousal before the probability task (Fig. 1 a). To characterize the emotion dimension dominance in terms of cognitive appraisals, we also we assessed cognitive appraisals of control, certainty and mastery beliefs.

In Study 2, we sought to experimentally replicate our findings from Study 1. Study 2, also preregistered, was conducted about one year after the onset of the COVID-19 pandemic. In Study 2 we experimentally induced emotional dominance using a subjective writing task, and asked participants to estimate the probability of a selection of the compound events from Study 1 (Fig. 1 c). Emotional dominance, valence and arousal were measured both before and after the emotion induction.

In both studies, participants also rated their anticipated risk of a COVID-19 infection over the course of a year. We included this measure to explore the dynamics of people's subjective infection risk perception over the course of the pandemic and to test whether the patterns of emotion-dependent probabilistic cognition were similar in neutral probability and realistic risk assessments.

The results from these studies extend our understanding of the role of emotions in human probabilistic cognition in the following ways:

1. We predicted and found that people's probability estimates for neutral compound events would be modulated by emotional dominance. Our results suggest that this emotion dimension affects the degree to which people show conservatism in their probability estimates. Participants high in emotional dominance gave more uniform probability estimates than participants low in emotional dominance. They tended to give relatively low estimates for high probability compound events and relatively high estimates for low probability compound events. Furthermore, we found that participants high in emotional dominance were more likely to use representativeness as a proxy for probability than participants low in dominance.

2. We found that dominance-specific conservatism transfers to realistic risk assessments. We analyzed prospective estimates for the risk of COVID-19 infection at two time points during the pandemic. At both time points, people gave higher estimates for long term compared to short-term infection risks, but this tendency was less pronounced in individuals reporting higher levels of emotional dominance. High dominance individuals gave lower estimates for a long term infection risk (the

high probability event) than individuals lower in dominance, resulting in relatively similar short- and long term risk estimates.

3. We characterized the little-understood emotion dimension dominance in terms of cognitive appraisals of certainty and control, mastery beliefs and the emotion dimensions valence and arousal. Dominance is positively associated with control appraisals and emotional valence and negatively associated with uncertainty appraisals. Our results suggest that emotional dominance may explain the previously reported effects of emotional valence and cognitive appraisals on probabilistic cognition.

Our work provides evidence that emotions not only affect probability estimates when outcomes are desired or undesired but also when probabilistic outcomes are affectively neutral. Whereas the emotion dimension valence has received a lot of attention in cognition-emotion research, the role of emotional dominance is not well understood. Our results suggest that people experiencing high emotional dominance make more conservative probability estimates and are more likely to base their assessments on representativeness than people experiencing low dominance. Our results also give insight into the psychological characteristics of the little-understood emotion dimension dominance, and show that dominance-specific probabilistic cognition generalizes to realistic contexts, as seen in the COVID-19 pandemic.

Results

Study 1

We asked participants to rate their current (state) and usual (trait) emotional valence, dominance and arousal, their anxiety and cognitive appraisals of uncertainty regarding the current situation and future developments, as well as subjective control associated with COVID-19, in the early stages of the pandemic (March and April 2020). In two tasks, participants estimated the probabilities of neutral compound events, i.e., the probabilities of sampling various three-item color combinations from known probability distributions (Fig. 1, e.g., BBB, BBY, BYY and YYY in Task 1, where B stands for the color blue and Y stands for the color yellow). Participants also rated the anticipated risk of a COVID-19 infection for time intervals up to one year in the future. The data sets as well as the code for statistical analyses are available on the Open Science Framework, as specified in the Data Availability Statement.

Participants reported lower average levels of emotional valence and dominance at the onset of the pandemic compared to their usual valence and dominance. Ratings of uncertainty and anxiety were generally high, and ratings of subjective control low. In both probability tasks, participants systematically overestimated the probability of compound events, except the compound event containing only the most probable kind of item (BBB). This overestimation was more pronounced in individuals reporting high emotional dominance. In comparison to participants low in dominance, these participants gave higher estimates for low probability compound events and also rated the most likely event as less likely. In other words, probability estimates of participants reporting high emotional dominance differed relatively little between high and low probability events. This effect can be interpreted as greater conservatism in high-dominance participants.

Was there also a relationship between dominance and representativeness? The most representative compound event (Kahneman and Tversky, 1972, p. 430) is the one that is most "similar in essential characteristics to its parent distribution"[10]. In our task, the key properties of the BBY sample are that it contains the colors of the underlying jar, and that the most frequent color in the underlying jar is the most frequent color in the sample. By contrast, BBB, despite being mathematically more probable, does not contain both colors, and is hence less representative than BBY. When asked to select the combination with

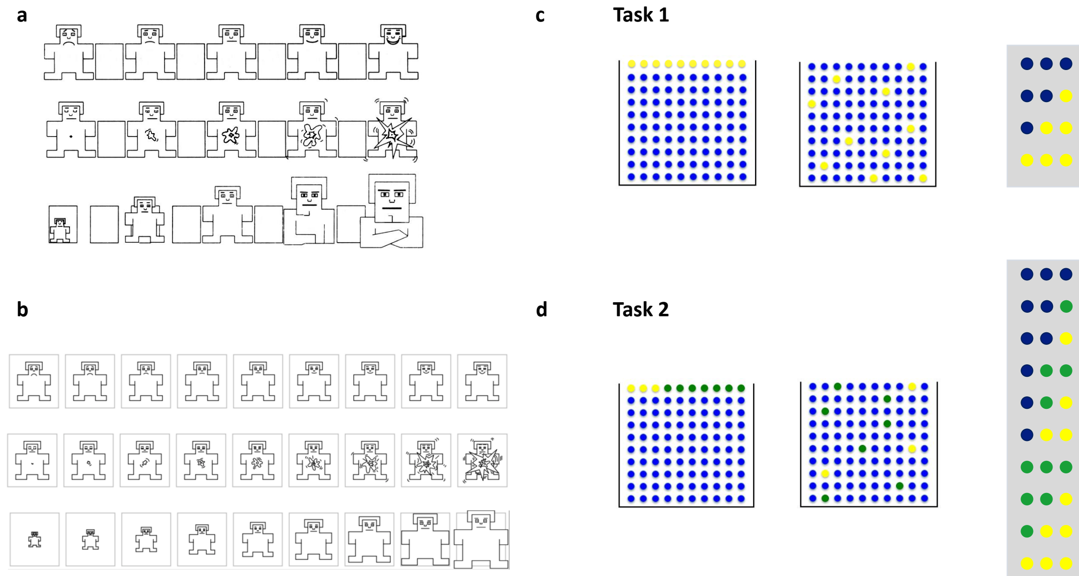

Figure 1. Material used in Studies 1 and 2. **a** Self-Assessment-Manikin Scales from Bradley & Lang (1994)[46] and Lang (1980)[47]. **b** Self-Assessment-Manikin Scales from PXLab[48]. **c** Probability Task 1: Ordered distribution (90 blue, 10 yellow), mixed distribution (90 blue, 10 yellow), queried compound events (BBB, BBY, BYY, YYY). **d** Probability Task 2: Ordered distribution (90 blue, 7 green, 3 yellow), mixed distribution (90 blue, 7 green, 3 yellow), queried compound events (BBB, BBG, BBY, BGG, BGY, BYY, GGG, GGY, GYY, YYY).

the highest probability, individuals higher in dominance showed a greater tendency to selected the most representative event over the mathematically most probable compound event.

Data preprocessing and statistical methods

Before analyzing participants' probability estimates, we tested whether belonging to a COVID-19 risk group affected participants' emotional state. Out of 162 participants, 24 indicated that they belonged to a risk group, 15 did not report whether they belonged to a risk group or not, and 123 indicated that they did not belong to a risk group. A MANOVA with risk group categorization as a predictor and state valence, dominance and arousal as outcome variables, as well as a two-sided Wilcoxon signed rank test showed that belonging to a risk group did not significantly predict participants' emotional state ($p > 0.1$). Thus, belonging to a risk group was not included as a variable in our subsequent analyses.

Unless explicitly stated, the predictors in our analyses were participants' raw responses on Likert scale variables. For visual presentation of results only, participants were categorized according to the level of their reported emotional valence, arousal and dominance, anxiety, and cognitive appraisals of uncertainty and control, so as to obtain roughly equally sized groups. Categories for anxiety and appraisals were low (a value below the median), median (exactly the median) and high (above the median). Further categories, in this case binary, were created to visualize the reported effect of the COVID-19 pandemic on participants' emotional state: increasing, meaning that the difference between usual and current emotional valence/dominance/arousal was positive or zero, and decreasing, meaning that the difference between usual and current emotional valence/dominance/arousal was negative.

We also applied a logit transformation to participants' probability estimates. Logit-transformed values indicate how extreme probability estimates are, and thus provide a more direct index of conservatism than can be seen in raw probability estimates[49,50]. The further a transformed value is from 0 (which is the log-odds of 50% or 0.5), the more extreme the probability estimate. Values closer to zero indicate greater conservatism, i.e., avoidance of extreme probability estimates. To avoid having infinite values in the analyses, and because the closest value participants could select on the slider to approximate the mathematically correct probability for compound event YYY (0.001) was 0, probability estimates of 0% were replaced by 0.001, and estimates of 100% were replaced by 99.999, resulting in log odds of -5 and 5, respectively. All analyses were conducted for both raw probability estimates and for logit-transformed values. Results were very comparable for the two types of analyses, although results for the logit-transformed values tended to be stronger. Because the raw probability estimates are easiest to interpret in reference to the probability task, we report those analyses here. Visualisations of analyses using logit-transformed data can be found in Supplementary Figures 3 and 4.

Estimates for affectively neutral compound probabilities

Participants rated the probability of different compound events in Tasks 1 and 2 (Fig. 1). We first analyzed how sensitive participants' probability estimates were to differences in the true probabilities of compound events. For this, we fitted separate linear models for Tasks 1 and 2, predicting respondents' *probability estimates* by the within subjects variable *queried compound event*. Boxplots of participants' probability estimates can be found in Supplementary Figures 3 and 4 (left columns).

In Task 1, the variance explained by *queried compound event* was $R^2 = 0.64$. The model's intercept, corresponding to BBB, was at 74.48 (bootstrapped 95% CI $[71.5, 77.45]$, $SE\,B = 1.51$). The beta weight for BBY was significantly negative (bootstrapped $B = -15.33$, 95% CI $[-19.15, -11.51]$, $SE\,B = 1.99$), as were the beta weights for BYY (bootstrapped $B = -50.17$, 95% CI $[-54.00, -46.35]$, $SE\,B = 1.95$) and YYY (bootstrapped $B = -63.96$, 95% CI $[-67.78, -60.14]$, $SE\,B = 1.96$). This means that participants' estimates for compound events containing at least one yellow item were significantly lower than estimates for the compound event containing only blue items. All Tukey's post hoc comparisons were significant (all $p < .0001$), indicating that differences between probability estimates were significant for all pairings of compound events. The main effect of *queried compound event* in Task 1 was significant in all subsequently fitted mixed linear models (all $p < .001$). These results show that in Task 1, participants were sensitivity to differences in the probabilities of the queried compound events.

Results were similar for Task 2: the variance explained by the within-subjects variable *queried compound event* was $R^2 = 0.55$. The model's intercept, corresponding to BBB, was at 73.72 (bootstrapped 95% CI $[70.88, 76.54]$, $SE\,B = 1.44$). The main effect of queried color combination on participants' probability estimates in Task 2 emerged in all subsequently fitted mixed linear models (all $p < .001$). While probability estimates for all compound events including at least one unlikely item differed from estimates for the high probability compound event BBB, Tukey's post hoc tests showed that not all contrasts were significant. Contrasts not significant under a p-value of 0.05 were: BGG-BGY, BGY-BYY, BYY-GGG, BYY-GGY, BYY-GYY, GGG-GGY, GGG-GYY, GGY-GYY, GYY-YYY. Effectively, this means that pairwise non-significant differences were mainly among the low-probability events, which differed relatively little in probability. Participants rated compound events with similar probability as relatively similar whereas they gave significantly different probability ratings for compound events that substantially differed in probability (see asterisks in the bottom row plots of Fig. 3 for the true probabilities of queried compound events in Task 2).

Next, we explored the relationship between emotional dominance and estimates of the neutral compound probabilities in Tasks 1 and 2. For each task, we fitted separate linear mixed models with respondents' *probability estimates* as the dependent variable, *queried compound events* as within-subjects repeated measures variables (4 queried events in Task 1, 10 in Task 2) and a) *current valence*, *current dominance* and *current arousal*, and b) *usual valence*, *usual dominance* and *usual arousal* as between-subjects

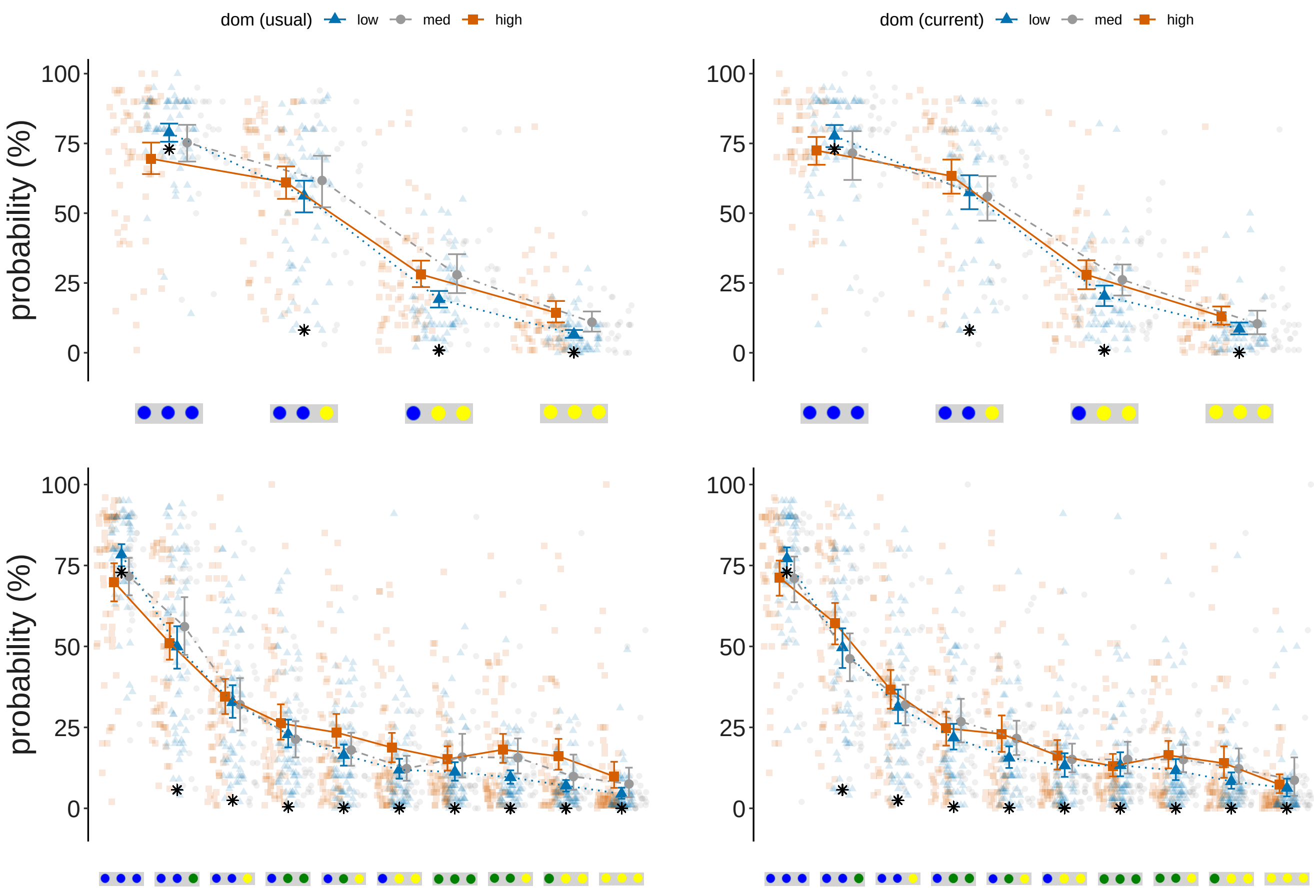

Figure 2. The plots display participants' probability estimates by emotional dominance in Study 1 for different compound events in Task 1 (top row) and Task 2 (bottom row). Queried compound events are plotted on the x-axis, ordered by magnitude of true mathematical probability (decreasing from left to right). The y-axis displays probability estimates in percent. True probabilities are indicated as black asterisks. Categories for emotional dominance are: low = values below the median; median = values exactly at the median; high = values above the median. Groups had approximately the same size. **Top row**: Compound probability estimates for Task 1. **Bottom row:** Compound probability estimates for Task 2. **Left column:** Participants' probability estimates by usual (trait) dominance before the onset of the Covid-19 pandemic (retrospectively reported). 95% *CI*s are displayed for each group. **Right column:** Participants' probability estimates by self-reported current (state) dominance at the onset of the Covid-19 pandemic (state dominance). 95% *CI*s are displayed for each group.

predictors. We included all three emotion dimensions to adjust for valence and arousal as covariates and to derive dominance-specific results. Here we report results for the more easily interpretable raw probability estimates. Plots for analyses using logit-transformed values can be found in Supplementary Figure 3.

In both tasks, *current dominance* and *usual dominance* modulated probability estimates (Fig. 2). When including *queried compound event*, *current valence*, *current dominance* and *current arousal* as predictors of probability estimates in a linear mixed model, we found a main effect of *queried compound event* ($F(3,474) = 472.69$, $p < 0.0001$) and an interaction between *current dominance* and *queried compound event* ($F(3,474) = 3.48$, $p = 0.02$) in Task 1 (top right plot in Fig. 2). In this model, the intercept, corresponding to *current valence*, *current dominance* and *current arousal* at 0 and the compound event BBB, was at 74.48 (bootstrapped 95% CI $[71.55, 77.41]$, $SE\ B = 1.51$). The beta weights for the interactions between *current dominance* and the compound events BBY (bootstrapped $B = 4.57$, 95% CI $[0.61, 8.54]$, $SE\ B = 2.06$, $p = 0.03$), BYY (bootstrapped $B = 6.06$, 95% CI $[2.09, 10.03]$, $SE\ B = 2.04$, $p = 0.003$) and YYY (bootstrapped $B = 5.12$, 95% CI $[1.16, 9.09]$, $SE\ B = 2.03$, $p = 0.01$) were significantly positive. In other words, participants reporting higher current (state) dominance gave lower estimates for the high probability compound event BBB, and they gave higher probability estimates for the low probability compound events BBY and BYY than participants scoring low on dominance. This indicates that participants feeling high in dominance avoided the extremes and gave more similar probability estimates, i.e. showed greater conservatism, than participants low in dominance.

A similar pattern, that is, a significant interaction between *dominance* and *queried compound event* ($F(3, 474) = 3.01$, $p = 0.03$) emerged for *usual dominance* (top left plot in Fig. 2): The model's intercept, corresponding to *usual valence*, *usual dominance* and *usual arousal* at 0 and the compound event BBB, was at 74.48 (95% CI $[71.54, 77.35]$, $SE\ B = 1.49$). Within this model, the beta weights for the interaction between *usual dominance* and the queried compound events BYY (bootstrapped $B = 6.14$, 95% CI $[1.74, 10.53]$, $SE\ B = 2.13$) and YYY (bootstrapped $B = 4.99$, 95% CI $[0.7, 9.43]$, $SE\ B = 2.23$) were significantly positive.

We had taken the COVID-19 pandemic as a naturally occurring manipulation of people's emotions. Thus, we were interested in the relationship between the self-reported emotional effect of the pandemic (the difference between *current* and *usual* emotions), and participants' probability estimates. In a linear mixed model predicting probability estimates by *queried compound event* and *dominance*, *valence* and *arousal difference*, *valence difference* interacted with *queried compound event* ($F(3, 474) = 2.58$, $p = 0.05$) in predicting probability estimates. This model had its intercept, corresponding to no change on all three emotion dimensions and the compound event BBB, at 74.48 (95% CI $[71.50, 77.39]$, $SE\ B = 1.51$). The beta weights for the interaction between *valence difference* and *queried compound event* were significantly negative for BYY (bootstrapped $B = -4.56$, 95% CI $[-8.52, -0.46]$, $SE\ B = 2.05$) and YYY (bootstrapped $B = -5.15$, 95% CI $[-9.1, -1.06]$, $SE\ B = 2.07$). This means that participants reporting lower *current valence* than *usual valence*, that is, who reported being emotionally more negatively affected by the pandemic, were more likely to be conservative in their probability estimates. At first sight, this result contradicts previous research showing that negative emotional states foster systematic information processing[27,29,51]. Yet one has to keep in mind that when looking at the *difference* between current (state) and usual (trait) emotional valence, we are considering trait and state emotional valence both at the same time. How exactly state and trait emotions interact has not fully been understood yet[52]. When analysed separately, current and usual emotional valence did not explain a significant part of the variance in probability estimates. Given that our result is only on the boundary of significance, we are reluctant to make claims about the modulating role of state-trait emotion interactions in subjective probability at this point.

In Task 2, most of these findings replicated (Fig. 2, bottom row). In addition to the main effect of queried item ($F(9, 1422) = 328.34$, $p < 0.0001$), there was an interaction between *current dominance* and *queried compound event* ($F(9,1422) = 2.35$, $p = 0.01$). The model predicting *probability estimates* by *queried compound event* and *current valence*, *current dominance* and *current arousal* had its intercept at 73.72 (bootstrapped 95% CI [70.88, 76.53], $SE\ B = 1.44$) corresponding to *current valence*, *current dominance* and *current arousal* at 0 and the *queried compound event* BBB. Overall, individuals high in *current dominance* gave relatively low estimates for the item BBB but relatively high estimates for all other queried items (bootstrapped B between 4.39 and 7.04, $SE\ B$ between 1.73 and 1.76). In this model, the beta weight for the main effect of *dominance* on probability estimates was also significantly negative (bootstrapped $B = -3.13$, 95% CI $[-6.06, -0.18]$, $SE\ B = 1.51$, $p = 0.04$). In other words, with increasing *current dominance*, individuals tended to give lower estimates for the high probability item and higher estimates for all other compound events, overestimating the probability of the low probability events. Effectively, they tended to give more similar answers for the different compound events (Fig. 2, bottom right). A similar pattern emerged for *usual dominance*: Besides a main effect of *queried compound event* on *probability estimates* ($F(9,1422) = 330.02$, $p < 0.0001$), *usual dominance* interacted with *queried compound event* ($F(9,1422) = 2.29$, $p = 0.02$) in predicting probability estimates. The model's intercept (*usual valence*, *usual dominance* and *usual arousal* at 0, compound event BBB) was at 73.72 (bootstrapped 95% CI [70.6, 76.2], $SE\ B = 1.43$). Within this model, we found interaction effects of *usual dominance* and *queried compound event* on estimates for all other compound events (bootstrapped B between 2.39 for BBG, and 6.63 for GYY, $SE\ B$ between 1.90 and 1.93), except for the item BBG. This means that the modulating role of dominance in probability estimates differed significantly between the high probability item BBB and all other items, except for BBG: For the high probability compound event BBB participants higher in dominance gave lower estimates and for the low likelihood compound events they gave higher estimates than participants scoring low on dominance. Neither *valence* nor *dominance* or *arousal difference* predicted probability estimates in Task 2 (all $p > 0.05$).

To test whether the association between emotional dominance and probability estimates also emerged on an individual level, we regressed the within-subjects variable *queried compound event* (compound events ordered by probability: BBB, BBY, BYY, YYY) on probability estimates (both raw values and logit-transformed values) for each participant individually. In a next step, we extracted participants' individual regression coefficients. Each regression coefficient tracks how much a single participant reacted to differences in compound events when estimating their probabilities. In Bayesian terms, when assuming an uninformative prior, this coefficient tracks how much participants react to the likelihood of compound events. In a frequentist framework, it quantifies how much a participants' probability estimates regress towards the mean. Because of the ordering of compound events from high to low, higher coefficients mean that people reacted less, estimating high and low probability compound events as relatively similar. That is, these participants avoided the extremes and showed greater conservatism. We then tested whether this participant-specific measure of conservatism was modulated by dominance. For this, we regressed *usual* and *current dominance* on this parameter (Regression Coefficient Analysis). Indeed, people higher in dominance had smaller beta weights, which means they gave relatively similar probability estimates. They reacted less to the likelihood or, in frequentist terms, regressed their estimates more towards the mean. A visualization of the results of this analysis can be found in Figure 3. The model predicting participants' regression coefficients by *usual dominance* was significant (for raw estimates: $F(1, 160) = 6.823$, $p = 0.01$, $R^2 = 0.03$; for logit-transformed estimates: $F(1, 160) = 5.38$, $p = 0.02$, $R^2 = 0.03$). The model predicting participants' regression coefficients by *current dominance* also explained a significant part of the variance (for raw estimates: $F(1, 160) = 5.14$, $p = 0.02$, $R^2 = 0.03$; for logit-transformed estimates: $F(1, 160) = 4.56$, $p = 0.03$, $R^2 = 0.02$). The model predicting participants' regression coefficients by *dominance difference* (*current* - *general dominance*) did not explain a significant share of the variance ($p > 0.05$). We ran the same analysis for probability estimates in Task 2. The model predicting participants' regression coefficients by *usual dominance* was significant (for raw probability estimates: $F(1, 160) = 4.08$, $p = 0.04$, $R^2 = 0.02$; for logit-transformed estimates: $F(1, 160) = 3.79$, $p = 0.05$, $R^2 = 0.02$). The model predicting participants' regression coefficients by *current dominance* was also significant (for raw probability estimates: $F(1, 160) = 5.58$, $p = 0.02$, $R^2 = 0.03$; for logit-transformed estimates: $F(1, 160) = 5.98$, $p = 0.02$, $R^2 = 0.03$). As for Task 1, *dominance difference* did not explain a significant share of the variance ($p > 0.05$).

Selection of the subjectively most likely compound event

Emotion theories predict that emotions characterized by positive valence and high certainty and control foster heuristic information processing. Accordingly, we expected increased heuristic information processing in participants reporting high emotional dominance relative to those reporting low dominance. A heuristic that has been reported in the previous literature in the context of subjective probability assessments of compound events is the representativeness heuristic[7,10]. Did participants high in dominance make more use of representativeness in their probability estimates than participants low in dominance?

To test this, we ran logistic regressions of participants' self-reported current and usual dominance on their choice for the most likely compound event in Task 1. More specifically, we contrasted choices for the compound event BBB (highest mathematical probability) and BBY (most representative). The results confirm a positive relationship between emotional dominance and the choice of the subjectively most likely compound event. The higher emotional dominance, the more likely a person was to select the most representative compound event over the mathematically most likely compound event. In a model predicting the selection of the most probable compound event by *usual dominance*, higher *usual dominance* (bootstrapped $B = 0.21$, $SE\ B = 0.11$, 95% $CI = [0, 0.43]$, $p = 0.05$, OR = 1.23, 95% CI = [1, 1.53]) made participants more likely to choose BBY over BBB as the most likely compound event. The same relationship was found for *current dominance* (bootstrapped $B = 0.20$, $SE\ B = 0.1$, 95% $CI = [0.02, 0.40]$, $p = 0.04$, $OR = 1.22$, 95% $CI = [1.02, 1.49]$).

Given previous evidence on the modulating role of valence in probabilistic cognition, we were also interested in whether emotional valence would likewise explain variance in participants' choices of the most likely compound event. *Usual valence* (bootstrapped $B = 0.29$, $SE\ B = 0.13$, 95% $CI = [0.07, 0.53]$, $p = 0.013$, OR = 1.33, 95% CI = [1.07, 1.69]) but not *current valence* ($p = 0.34$) predicted the selection of the most likely compound event, with participants reporting more positive *usual valence* being more likely to select the most representative compound event as the most likely item. We ran the same analyses for participants' choices of the most likely compound event in Task 2 (contrasting choices for BBB and BBG). Results were less pronounced but went in the same direction for dominance (*current dominance*: $OR = 1.22$, $p = 0.06$, 95% $CI = [1, 1.50]$; *usual dominance*: $OR = 1.2$ $p = 0.1$, 95% $CI = [0.97, 1.50]$). For valence, they were more pronounced (*current valence*: $OR = 1.28$ $p = 0.025$, 95% $CI = [1.04, 1.6]$; *usual valence*: $OR = 1.39$ $p = 0.07$, 95% $CI = [0.1, 0.58]$).

Study 2

In Study 1, participants reporting high emotional dominance gave more similar probability estimates for high and low probability compound events relative to participants reporting low emotional dominance. In other words, the degree to which participants tended to be conservative and avoid extreme probability estimates was positively associated with dominance both on a group and an individual level. Furthermore, participants high in emotional dominance and valence were more likely to choose as most likely a representative compound event (BBY in Task 1 and BBG in Task 2) over the compound event with the highest mathematical probability. However, the correlational nature of Study 1 does not allow any causal inference about the relationship between emotional dominance and probabilistic cognition.

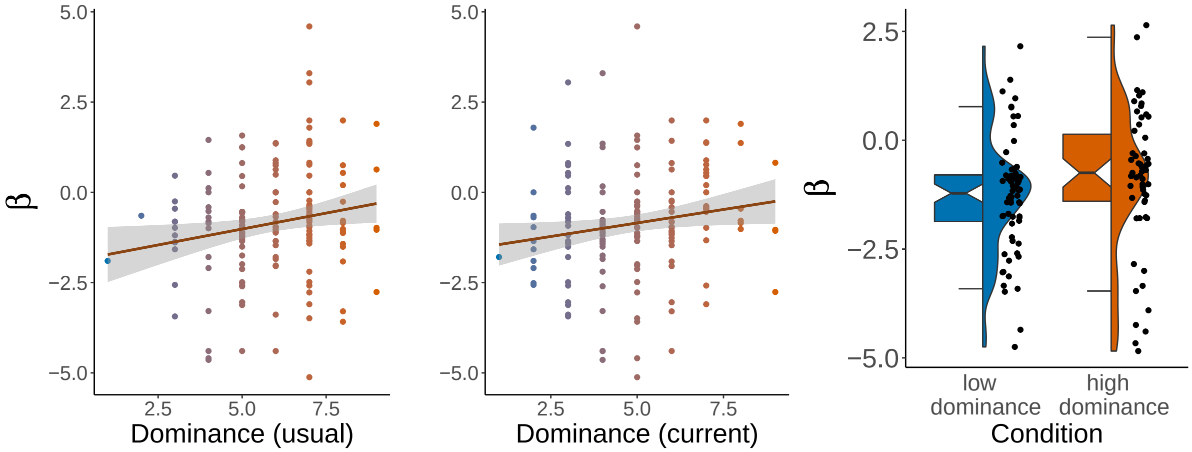

Figure 3. The plots visualize the relationship between individuals' conservatism and emotional dominance in Studies 1 and 2. **Left (Study 1):** Scatterplot and regression line with standard error for the relationship between participants' self-reported usual dominance and regression coefficients extracted from the model predicting logit-transformed probability estimates by *queried compound event*. **Center (Study 1):** Scatterplot and regression line with standard error for the relationship between participants' self-reported current dominance and regression coefficients extracted from the model predicting logit-transformed probability estimates by *queried compound event*. **Right (Study 2):** Effect of the emotion manipulation (high vs. low dominance) on regression coefficients extracted from the model predicting logit-transformed probability estimates by *queried compound event*. The plot shows notched boxplots, data distributions and individual data points in each experimental condition (left/green: low dominance, right/red: high dominance

In Study 2 we therefore replicated the key components of Study 1, using an experimental manipulation of emotional dominance. Participants were randomly assigned to one of two conditions in an autobiographical writing task that was designed to induce high or low emotional dominance. Results suggest a causal effect of emotional dominance on neutral compound probability estimates.

Participant characteristics and manipulation check

Experimental groups did not differ in their self-reported proficiency in mathematics (low dominance condition: $N = 64$, $M_{prof} = 2.67, SD = 0.87$, high dominance condition: $N = 55$, $M_{prof} = 2.64, SD = 0.95$); the proportion of participants with a previous COVID-19 infection (9.4% in the low dominance condition, 12.7% in the high dominance condition); in gender distribution (15.9% males in the low dominance condition, 12.7% males in the high dominance condition) or in proportion of participants vaccinated against COVID-19 (87.5% not vaccinated in the low dominance condition, 94.5% in the high dominance condition). Thus, these variables were not included as control variables in subsequent analyses.

To test the effectiveness of the emotion manipulation, we compared dominance, valence and arousal ratings after the emotion induction, as well as differences between ratings before and after the emotion induction (change scores) between conditions. After the emotion induction, emotional dominance was higher in the high dominance condition ($M_{post} = 5.6$, $SD = 1.76$) than in the low dominance condition ($M_{post} = 4.61$, $SD = 1.82$; $W = 2339.5$, $p = 0.002$, $d = 0.2$). Dominance change scores were computed by subtracting pre from post emotion induction scores. Dominance increased in the high dominance condition ($M_{change} = 0.64$, $SD = 1.98$) but did not in the low dominance condition ($M_{change} = -0.1$, $SD = 1.78$). This difference in change scores was significant ($W = 2125.5$, $p = 0.05$, $d = 0.13$). Emotional valence was also higher in the high dominance condition ($M_{post} = 5.49$, $SD = 1.6$) than in the low dominance condition ($M_{post} = 4.72$, $SD = 1.77$; $W = 2248$, $p = 0.008$, $d = 0.17$). The change in valence significantly differed between groups ($W = 2276.5$, $p = 0.005$, $d = 0.18$): In the high dominance condition valence change was positive ($M_{change} = 0.05$, $SD = 1.89$) whereas in the low dominance condition it was negative ($M_{change} = -0.64$, $SD = 1.42$). Experimental groups did not differ in emotional arousal after the emotion induction ($W = 1874$, $p = 0.54$) or in arousal change ($W = 1926$, $p = 0.37$). These findings strongly suggest that the emotion manipulation was successful. They also replicate the positive association between emotional dominance and valence we found in Study 1.

Emotional dominance affects neutral probability estimates

Statistical packages and analysis methods were the same as in Study 1 (Methods). To test the effect of the emotion induction on probability estimates, we fitted a linear mixed model predicting probability estimates by *queried compound event* and *emotion condition*. A type III ANOVA of the mixed model revealed a main effect of *queried compound event* ($F(3,351) = 437.73$, $p < 0.0001$) and an interaction effect of queried compound event and emotion condition ($F(3,351) = 2.63$, $p = 0.05$) on participants' probability estimates. The results were similar for logit-transfomed values ($F(3,351) = 2.7$, $p = 0.05$). Experimentally replicating findings from Study 1, we found that participants in the high dominance condition gave more similar probability estimates for the high and low probability compound events compared to participants in the low dominance condition (see Fig. 4). Marginal R^2 of this model was 0.72, with an intercept (color combination BBB in the high dominance condition) at 74 (bootstrapped 95% *CI* $[71.05, 77.00]$, $SE\ B = 1.50$). Within this model, the beta weight for *condition [low dominance]* was significantly negative (bootstrapped $B = -5.03$, 95% CI $[-9.21, -0.85]$, $SE\ B = 2.15$). The weight for the interaction between compound event BYY and *condition [low dominance]* was significantly positive (bootstrapped $B = 7.32$, 95% *CI* $[1.68, 12.95]$, $SE\ B = 2.87$), as was the beta weight for the interaction between compound event YYY and *condition [low dominance]* (bootstrapped $B = 6.68$, 95% *CI* $[1.04, 12.31]$, $SE\ B = 2.87$). Compared to participants in the low dominance emotion condition, participants in the high dominance emotion condition gave lower estimates for the high probability compound event BBB and higher estimates for the low probability compound events BYY and YYY. In other words, inducing a high dominance emotional state increased participants' tendency to show conservatism in probability estimates for affectively neutral compound probabilities.

As in Study 1, we next tested whether emotion condition also had an effect on probability estimates for the different compound events on an individual level. For this, we extracted regression coefficients for each participant individually (Regression Coefficient Analysis, regressing *queried compound event* on *probability estimates* as in Study 1), both for logit-transformed and raw probability estimates. We then tested whether the difference in regression coefficients between conditions was significant using the two-sided Wilcoxon signed rank test. For raw probability estimates, regression coefficients in the high dominance condition were descriptively less negative ($M_{coef} = -17.42$, $SD = 28.94$) than in the low dominance condition ($M_{coef} = -23.39$, $SD = 25.25$), but this difference was not significant ($W = 2058$, $p = 0.11$). For logit-transformed probability estimates (reflecting the extremeness of probability estimates), regression coefficients in the high dominance condition were significantly less negative ($M_{coef} = -0.91$, $SD = 1.64$) than in the low dominance condition ($M_{coef} = -1.3$, $SD = 1.33$, $W = 2161$, $p = 0.03$, $d = 0.14$). A visualization of this result can be found in Fig. 3. In other words, in the high dominance condition individual logit-transformed slopes were less steep and regression coefficients more centered around 0. An increase in emotional dominance made people's probability estimates more conservative, that is, decreased the difference between estimates for high and low probability compound events.

Emotional dominance affects the selection of the subjectively most likely compound event

In Study 1 high dominance individuals were more likely than low dominance individuals to evaluate probabilities based on representativeness. Thus, in a subsequent step, we analyzed participants' selection of the subjectively most likely compound event as a function of emotion condition. For this, we computed a logistic regression with *emotion condition* as predictor and participants' choice of the subjectively most probable compound event (contrasting BBB = highest likelihood and BBY = highest representativeness). Participants in the low dominance condition had a higher likelihood of choosing BBB over BBY as the most likely compound event than participants in the high dominance condition (see Fig. 4, bootstrapped $B = 0.64$, $SE\ B = 0.27$, $p = 0.02$, 95% CI $[0.11, 1.19]$; $OR = 1.9$, 95% CI $[1.11, 3.29]$). In other words, participants in the high dominance condition were more likely to choose the more representative compound event over the mathematically most likely one. These results confirm our findings from Study 1, that is, that emotional dominance is positively associated with the use of representativeness as a proxy for probability. Our findings further imply that this relationship is causal: emotional dominance affects how people derive probabilities. Increased emotional dominance makes it more likely that a person bases her evaluations on representativeness instead of on the axioms of probability.

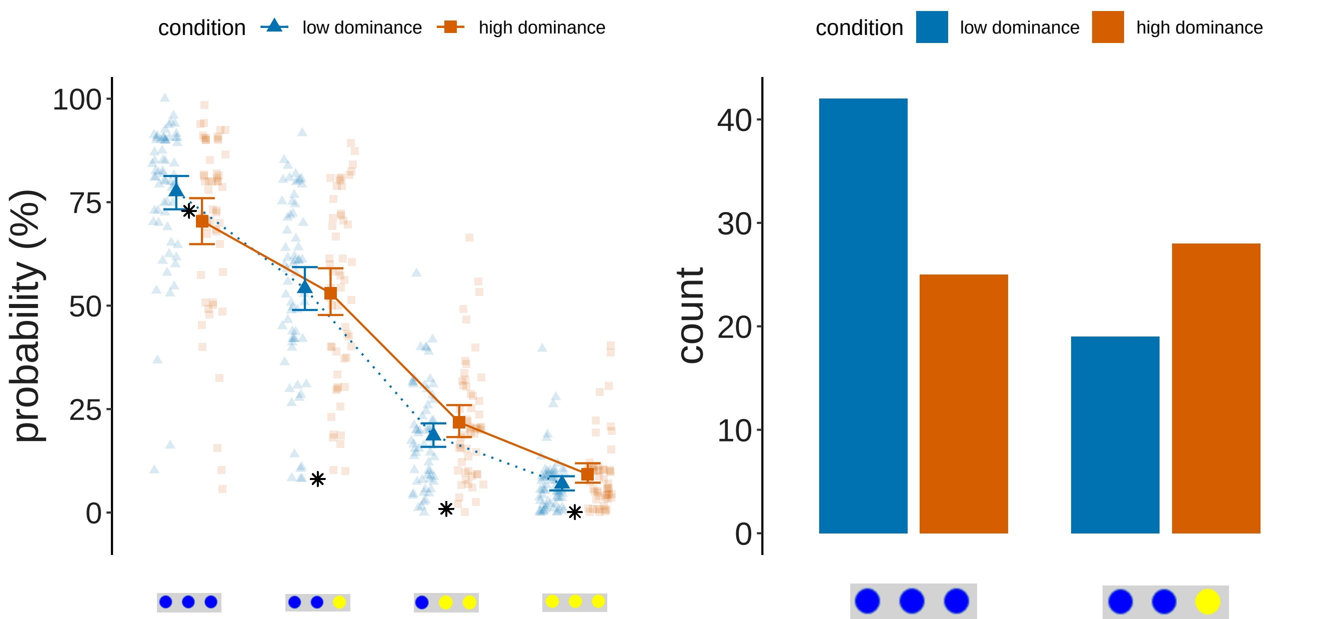

Figure 4. Emotional dominance affects conservatism and the use of representativeness as a proxy for mathematical probability. **Left:** Line chart displaying probability estimates in percent for the queried compound events by experimental condition (low vs. high dominance). True probabilities are indicated as black asterisks. Mean values and 95% *CI*s are displayed for each group. **Right:** Selection of the subjectively most likely compound event by experimental condition (low vs. high dominance). Low-dominance participants had a greater rate of selecting the objectively most probable event (BBB) as most likely. High-dominance participants, in comparison to low-dominance participants, had a greater tendency to select the representative event (BBY) as most probable.

Dominance-specific conservatism transfers to realistic risk assessments

Next, we investigated whether the patterns we found for dominance-specific conservatism would transfer to realistic risk assessments. We asked participants at the onset of the COVID-19 pandemic (Study 1) and one year into the pandemic (Study 2) to indicate their prospective estimates in percent for the risk of them being infected with COVID-19 within the next *3 days*, *week*, *month*, *3 months*, and *year*. First, we fitted a linear mixed model with *study* as the between-subjects predictor, queried *time interval* as the within-subjects predictor, and *risk estimates* as the dependent variable, to test whether infection risk perceptions had changed over the course of the pandemic. We found significant main effects of queried *time interval* ($F(4,1056) = 61.81$, $p < 0.0001$) and *study* ($F(1,264) = 5.58$, $p = 0.02$). In both studies, participants gave higher risk estimates with increasing length of time interval, and in Study 2 risk estimates were generally higher (Fig. 5, left plot). Thus, *study* was included as a control variable in subsequent analyses. Because of the shared variance between emotional dominance and valence, we also included emotional valence as a control variable in our analyses. In a next step, we analyzed the relationship between emotional dominance and conservatism in participant's COVID-19 infection risk estimates. More specifically, we tested whether the pattern we found for dominance-specific conservatism in neutral compound probability estimates would generalize to COVID-19 risk estimates. We aggregated data from both studies and fitted a linear mixed model with *study*, *current dominance* and *current valence* as well as the interaction between these emotion variables and the within-subjects variable *time interval* as predictors and *risk estimates* as the dependent variable. In this model, the effect of *time interval* was significant ($F(4,1052) = 11.65$, $p < 0.0001$), as was the effect of *study* ($F(1,262) = 6.27$, $p = 0.013$). There was also a main effect of valence ($F(1,262) = 5.38$, $p = 0.02$): Participants reporting lower emotional valence at the time of the study generally gave lower risk estimates for a COVID-19 infection. Furthermore, the interaction between *current dominance* and *time interval* was significant ($F(4,1052) = 3.67$, $p = 0.005$). We conducted the same analysis for *usual dominance* and *valence*. In this model, neither *dominance* nor *valence* predicted risk estimates beyond *study* and *time interval* (all $p > 0.05$). These results reproduce the pattern we found for neutral compound probability estimates, suggesting that the modulating role of current (state) emotional dominance in probabilistic cognition transfers to realistic contexts such as the COVID-19 pandemic. Irrespective of emotional valence, participants experiencing high emotional dominance showed increased conservatism, giving more similar risk estimates for longer and shorter time intervals. An interpretation of this finding is that emotional dominance modulates cognitive processes on a fundamental level, manifesting itself both in probability estimates of neutral compound events as well as risk estimates in realistic contexts. Alternative interpretations are discussed in the Discussion section. A visualization of these relationships can be found in Fig. 5. We also provide a more detailed analysis of participants' risk estimates in Supplementary Analyses 2.

Emotional rationality: Considering emotional dominance in probabilistic cognition

Over the past decades of research on the modulating role of emotions in cognitive processes[56], the emotion dimension dominance has received relatively little attention. This is surprising, given its usefulness for differentiating between emotions that share the same valence and arousal (e.g., anger and anxiety)[57], its distinct neural representation[43] and its conceptual proximity to both valence- and appraisal-centered emotion theories.

Our results suggest that emotional dominance is an important contributor to variability in probabilistic cognition. But what exactly is emotional dominance? To better understand the general cognitive and emotional patterns associated with emotional dominance, and to characterize emotional dominance in relation to leading psychological theories of emotion and cognition, we investigated the relationship between emotional dominance, the emotion dimensions valence and arousal, and appraisals of certainty and control. These data were collected in Study 1. Dominance was positively associated with valence ($p = 0.0001$, $r = 0.29$) and *control* ($p = 0.002, r = 0.24$) and negatively associated with *current uncertainty* ($p = 0.02, r = -0.18$) and *future uncertainty* ($p = 0.01, r = -0.2$). A visualization of the correlations can be found in the correlation plot in Supplementary Figure 2; a more detailed analysis of the relationship between emotions and cognitive appraisals is provided in Supplementary Analyses 1. Previous research has found that a) emotional valence[22,27–30] and b) appraisals of certainty and control[17,18,26] modulate cognitive processes and affect risk estimates. So far, these strands of research have been separated. Our finding, i.e., that an increase in emotional dominance makes people more conservative in their neutral

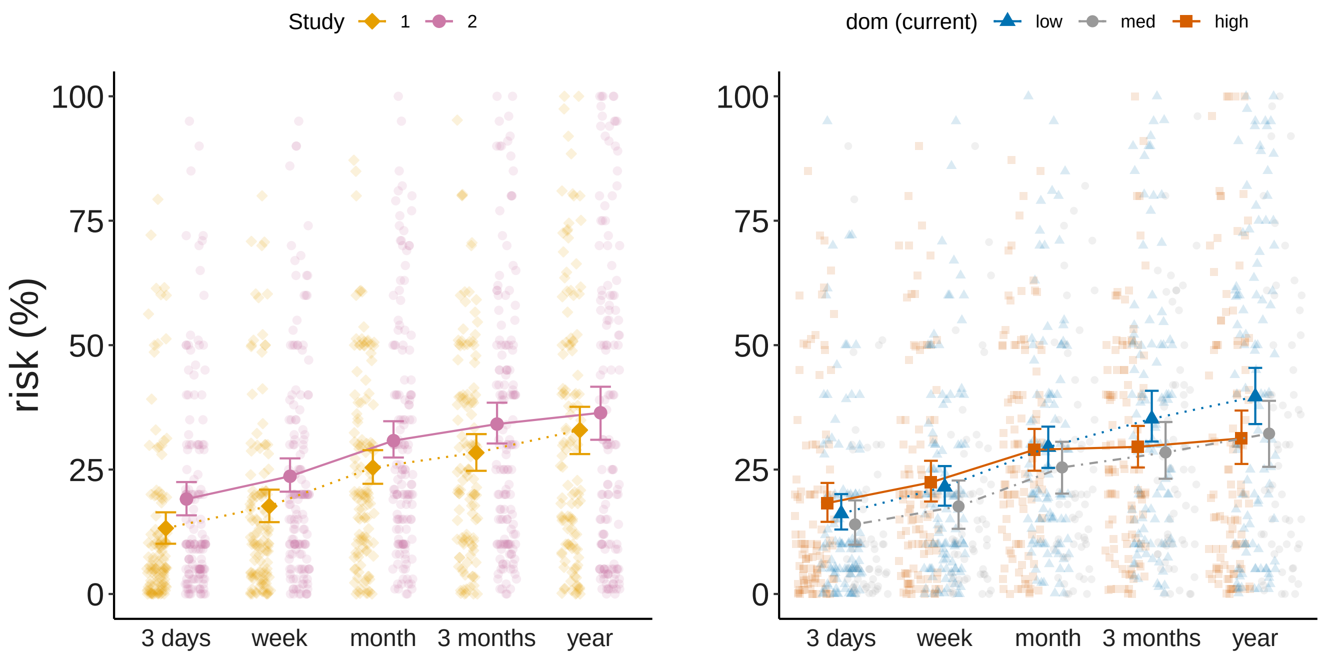

Figure 5. COVID-19 infection risk estimates differed between Studies 1 and 2 (left); dominance-specific conservatism transferred to realistic risk assessments (right). **Left:** Line chart displaying prospective COVID-19 infection risk estimates at the onset of the Covid-19 pandemic (Study 1) and one year into the pandemic (Study 2). Risk estimates were generally higher at the onset of the pandemic than one year into the pandemic. **Right:** Line chart displaying COVID-19 infection risk estimates by current dominance (aggregate data from Studies 1 and Study 2). Participants high in current emotional dominance gave more optimistic long term infection risk estimates than participants low in emotional dominance. As for neutral probability estimates, emotional dominance was positively associated with conservatism in realistic infection risk estimates, the tendency to give more similar short- and long term risk estimates.

probability and realistic risk assessments and fosters the use of representativeness as a proxy for probability, supports the view that emotional dominance may be the unifying concept explaining previously reported effects of emotional valence and appraisals of certainty and control on probabilistic cognition.

How can we interpret our findings in light of existing theories of probabilistic cognition? One possibility, in line with the Probability Theory Plus Noise model (PT+N)[15], would be that participants high in dominance experienced more noise in the probability estimation process, resulting in stronger deviations from probability theory. A potential source of this noise would be arousal; however, we did not find elevated levels of arousal in high dominance individuals. Another model that explains human probabilistic inference is the Configural Weighted Average model (CWAM[58,59]). According to this model, people infer compound probabilities by first weighting individual probabilities, with larger weights put on small probabilities, and then adding them up. Yet these weights may not be stable across participants but may instead vary with individual differences and situational influences, such as emotional dominance. From a Bayesian standpoint, individuals' probability estimates are based on continuous sampling and belief updating[14,49]. An important assumption in this context is that deviations from Bayes's rule (and from probability theory in general) stem from people's rational adaptations to their limited computational resources: People constantly optimize their cognitive toolbox for probabilistic Bayesian inference by learning to infer[49]. Learning occurs over time and may be subject to psychological and environmental influences, giving individuals the opportunity to differentially optimize their probabilistic inference machine for distinct psychological contexts. Such adaptations may occur in different stages of the probabilistic inference mechanism: the sampling itself or the updating process may be affected. What might it mean if mental sampling were modulated by emotional dominance? In our studies, participants were confronted with a visual representation of a generating probability distribution and had to infer different compound probabilities. According to the Bayesian Sampler model[14], in situations like this people engage in sampling from memory in order to arrive at a subjective probability estimate. If someone already feels confident, certain and in control, then investing cognitive resources into continued sampling would be wasteful and inefficient if a judgment feels already good enough. In contrast, if a person lacks confidence, certainty and control, continuing mental sampling promises to pay off as it decreases feelings of uncertainty and increases feelings of subjective control. Yet sampling may also differ qualitatively between high and low dominance individuals. For instance, different information may come to mind depending on the emotional state someone is in. In previous studies testing the effect of stimuli valence on memory encoding and retrieval, positive valence caused broadening of memory storage and retrieval[60,61]. In our tasks, more rare events (i.e., the low probability items) may have come to mind in participants in a high dominance emotional state (which was also characterized by more positive valence), resulting in an overestimation of the probability of unlikely events. This overestimation may in turn increase probability ratings for compound events containing rare elementary events and a tendency to subjectively perceive the "representative" compound event as most likely. A second interpretation within a Bayesian framework is that emotional dominance modulates how much attention people pay to the prior or the likelihood in the Bayesian updating process. Participants high in dominance may focus more on the prior and weight sampled evidence relatively little, resulting in conservative probability estimates. Within this interpretation, high emotional dominance may provide something like "immunity" against incoming evidence. In this view, a person high in dominance would generally assume stability of her view of the world and thus expect her beliefs to change relatively little over time.

Discussion

Across two studies we found evidence supporting the hypothesis that the emotion dimension dominance modulates probabilistic cognition on a fundamental level. Emotional dominance is characterized by how controlling, influential, in control, important, dominant and autonomous a person feels. Participants high in emotional dominance gave relatively low estimates for high probability and relatively high estimates for low probability events. In other words, the differences between estimates for the most probable and less probable events were smaller for people high in dominance. This can be viewed as a form of conservatism[12,13,62]. Despite the theoretically very different nature of assessing risk of real-world events, we found the same pattern for realistic risk assessments, where participants higher in emotional dominance gave more optimistic long term COVID-19 infection risk estimates that participants lower in emotional dominance. An increase in emotional dominance also made people more likely to select the most representative over the mathematical most likely event when selecting the most probable out of a number of probabilistic events. This result can be interpreted as an increased tendency to use representativeness as a proxy for probability.

Going beyond previous work on the role of emotions in probabilistic cognition[22,23,26], we assessed participants' probability evaluations in neutral probability estimation tasks. This allowed us to quantify the effect of emotions on probability assessments without the potentially distorting influence of the desirability of probabilistic outcomes. Our results demonstrate that emotions have a fundamental modulatory role in thinking, even shaping perception of affectively neutral probabilistic events.

We have considered how the modulating role of emotional dominance and valence in probabilistic cognition could be explained in the context of existing cognitive models of probabilistic inference. More specifically, we focused on the Configural Weighted Averages Model[58,59], the Probability Theory plus Noise Model[15], and Bayesian accounts of probabilistic cognition[14,49]. At this point, our consideration of possible cognitive processes underlying dominance-specific probabilistic cognition is purely theoretical. Hierarchical Bayesian modeling[59] could be used to better understand the mechanisms causing the dominance-induced patterns we found in people's probability estimates, comparing the predictive power of different models of dominance-specific conservatism in probabilistic inference. A challenge here would be to find the appropriate adaptations of the models to account for variations in dominance. Another approach would be to use a sequential sampling paradigm and estimate the sampling parameters of individuals high and low in dominance. Given that the PT+N model and the Bayesian sampler model make similar predictions in many situations, a linear regression approach[63] appears promising in this context. To test whether high and low dominance and valence individuals differ in the relative attention paid to prior and likelihood in the Bayesian updating process, future work could directly manipulate the strength of the prior vs. the likelihood.

Our finding that dominance-specific conservatism transferred to realistic COVID-19 infection risk assessments raises additional question about the interpretation of the role of dominance in probabilistic cognition. In contrast to the probability tasks, for which objectively correct answers exist, it is impossible to know individual participants' true risk of a future COVID-19 infection. Thus, we cannot make any statements about the accuracy of participants' estimates for the risk of a COVID-19 infection. What we can say, however, is that participants reporting high emotional dominance gave relatively similar short and long term infection risk assessments. Besides a general dominance-induced cognitive mechanism, a psychological explanation for this finding is that high dominance individuals might feel less in the grip of the pandemic and have a more optimistic mindset compared to low dominance individuals. It could also be that people high in dominance had greater ability to take measures against an infection (e.g., working from home, rather than in a public setting with high infection risk) compared to people low in dominance. Yet it might also be the case that the general conservatism bias we found for neutral probability assessments transfers to real-life scenarios.

So far we mainly focused on explanations for the effects we found by looking at high dominance. Yet, one can also approach this issue from the other direction. Low emotional dominance may be associated with increased hesitation, careful assessment of information and decreased confidence in one's assessments. This would explain why low dominance is associated with less heuristic probability assessments and an increased sensitivity to differences in the probabilities of compound events. Regarding risk assessments, the same mechanism could explain more pessimistic infection risk assessment in the context of the COVID-19 pandemic in low dominance individuals, who predicted that the risk of an infection would still be increasing one year into the future. More research is needed to better understand the role of emotional dominance in probability assessments in different contexts, for example for evaluations of elementary events, conditional probabilities and function learning.

Emotional dominance has received relatively little attention in previous research on the relationship between emotions and cognition. One reason for this might be that dominance has typically been found to explain less variance in people's emotional reactions to environmental stimuli than valence and arousal[39]. Yet emotional dominance is needed to differentiate between emotions, for instance anger and anxiety[57], that have the same valence and arousal patterns. Our results support the hypothesis that beyond sharing variance with emotional valence, emotional dominance is characterized by unique patterns of cognitive appraisals, with high emotional dominance being associated with increased levels of subjective control and certainty. We found that emotional dominance was key for predicting conservatism, both in affectively neutral probability and real-world risk assessment, as well as the use of the representativeness in people's probability estimates. This insight is of great value given the current global challenges such as climate change and the COVID-19 pandemic. Our findings also suggest that emotional dominance may be the unifying construct explaining previous research on the effect of emotional valence and cognitive appraisals on human thinking and decision making.

Methods

Participants

In Study 1, N = 164 undergraduate psychology students from the University of Surrey and participants recruited on social media and research networks participated, out of which 162 produced valid data entries (M_{age} = 25.12, range 18-88, 33 male). Study 2 had N = 121 participants, with N = 119 complete and usable data files (N = 38 master's conversion psychology students and N = 81 undergraduate psychology students from the University of Surrey, M_{age} = 21.75, range 18-49, 18 male). Both studies were conducted fully online via Qualtrics and SoSciSurvey software. Participation was voluntary without reimbursement. In both studies, the experiment was part of a lab session, a voluntary part of a cognitive psychology course. An exclusion criterion for participation in Study 1 was a previous COVID-19 infection. Both studies were conducted in accordance with the Declaration of Helsinki and the ethical guidelines of the University of Surrey, UK.

Procedure

In Study 1, participants first gave informed consent online. Then participants estimated their risk of getting infected with COVID-19 (in percent) in the next three days, week, month, three months and year. Subsequently, participants rated their appraisals of current and future uncertainty, control, mastery and anxiety associated with the COVID-19 infection. Furthermore, personal consequences of a COVID-19 infection were assessed: *In case of an infection, the consequences for me personally would be ...* with the answer options 1 = *not even noticeable*, 2 = *noticeable*, 3 = *affecting me a bit*, 4 = *affecting me a lot*, 5 = *serious*. Participants also indicated whether they belonged to a risk group (*Are you over 60 years old or do you have existing health conditions that put you in a higher risk group for COVID-19?*). Next, participants rated their usual (trait) and current (state) emotional arousal, dominance and valence on the Self-Assessment-Manikin Scales[46]. Subsequently, participants completed two probability tasks, asking them to give probability estimates for drawing different color combinations with replacement from jars filled with 100 balls of two (Task 1) and three (Task 2) different colors (Fig. 1). Finally, basic demographic data (age, gender, country of residence) was collected.

In Study 2, participants first gave informed consent online. They rated their usual (trait) and current (state) emotional dominance, valence and arousal on nine-point Self-Assessment-Manikin[46] scales. Participants were randomly assigned to either the high or low dominance emotion condition and completed a subjective writing task to induce high or low dominance, as described below. After the emotion induction, participants rated their subjective risk of an infection with COVID-19 over the course of a year and completed probability Task 1. Instructions were similar as in Study 1: participants were asked to rate the probabilities of drawing blue-blue-blue (BBB), blue-blue-yellow (BBY), blue-yellow-yellow (BYY) and yellow-yellow-yellow (YYY) from an urn filled with 90 blue and 10 yellow marbles with replacement. Participants additionally indicated their age and gender, whether they had already been vaccinated against COVID-19 (answer options: *Yes, I got the first shot*; *Yes, I got both shots*; *No, I did not get vaccinated yet*), whether they had been diagnosed with COVID-19 in the past (answer options: *Yes*, *No*) and how proficient they were in mathematics and statistics (answered on a 5-point Likert scale going from 1 = *Not at all* to 5 = *an expert*).

Cognitive appraisals

Participants rated their subjective appraisals of current and future uncertainty, control, mastery and anxiety on seven-point Likert scales in randomized order. Instructions were: *Please indicate how much you agree to the following statements: Considering the current developments associated with COVID-19 ...* 1) *I am anxious that close ones or I get infected with COVID-19*, 2) *I feel uncertain about what is going on at the moment*, 3) *I feel I have control over the situation*, 4) *I can master challenges associated with COVID-19*, 5) *I am uncertain about the future developments associated with COVID-19*.

Emotion measure

Emotional valence, arousal and dominance were assessed using the nine-point version of the Self-Assessment-Manikin scales[46,47]. Instructions were based on material provided by the authors. Instructions for the Valence scale were: *The following scale shows 9 different levels of emotional valence. If you select the first figure you indicate that you feel completely unhappy, annoyed, unsatisfied, melancholic, despaired, bored and if you select the last figure you indicate that you feel completely happy, pleased, satisfied, contented, hopeful. You can select any answer option between the extremes to indicate intermediate levels of emotional valence.* Instructions for the Arousal scale were: *The following scale shows 9 different levels of emotional arousal. If you select the first figure you indicate that you feel completely relaxed, calm, sluggish, dull, sleepy, unaroused and if you select the last figure you indicate that you feel completely stimulated, excited, frenzied, jittery, wide-awake and aroused. You can select any answer option between the extremes to indicate intermediate levels of emotional arousal*. Instructions for the Dominance scale were: *The following scale shows 9 different levels of emotional dominance. If you select the first figure you indicate that you feel completely controlled, influenced, cared for, awed, submissive, guided and if you select the last figure you indicate that you feel completely controlling, influential, in control, important, dominant, autonomous. You can select any answer option between the extremes to indicate intermediate levels of emotional dominance*. For each scale, participants were first asked to indicate their usual (trait) emotion (*Please indicate which of the pictures best describes how you usually feel*) and then to indicate their current (state) emotion (*Please indicate which of the pictures best describes how you feel right now*). In Study 1, visual stimuli were from the PXLab website of the University of Mannheim[48]. For these stimuli each answer option corresponds to one particular manikin, thus the last sentence of the instructions (*You can select any answer option between the extremes to indicate intermediate levels of emotional dominance*) was deleted. In Study 2, visual stimuli by Lang (1980)[47] were used (Figure 1).

Emotion induction

In Study 2, high and low emotional dominance were induced using a subjective writing task[26,64]. The instructions were as follows: *In the following we ask you to think and write about three situations which could be real or imagined. Please describe these situations in 2-3 sentences each. Then we will ask you to write about one of these situations in more detail. Space for writing will be provided on the next page. Do not write about anything which may identify you or someone else. Only write about something you feel comfortable to share*. Each individual subtask was instructed: *Please think of a situation in which you would feel very [...]. Describe this situation in 2-3 sentences using the entry box below.* In the high dominance condition, participants were instructed to write about situations in which they would feel 1) *angry*, 2) *furious and outraged*, 3) *in control and dominant*, 4) *strong and autonomous* and 5) *influential and important*. In the low dominance condition, participants were instructed to write about situations in which they would feel 1) *anxious*, 2) *scared*, 3) *controlled and influenced*, 4) *weak and cared for* and 5) *awed, submissive and unimportant*. Upon completion of this writing task, participants completed a second writing task with the instructions: *Please think again of the situations you just described. Please choose* *the situation which was emotionally most intense. Please describe in more detail (5 sentences) how you felt in that situation (e.g., physiologically, emotionally, behaviourally, cognitively) so that a person reading it would feel the same way.* In the first lab session (*N* = 37 students), instructions slightly differed from this method: subtasks $3) - 5)$ were grouped and participants were asked to write about this emotion-eliciting event in more detail. Groups did not differ in induced emotional dominance between data collection time-points (both when analysing change scores and emotional dominance after the emotion induction), thus data were pooled.

Risk task

Participants rated their infection risk using a slider. The scale ranged from 0 to 100 (increments of 1 in Study 1, increments of 0.233/0.232 in Study 2). Participants were asked: *What do you think is your personal risk in % of being infected with COVID-19 ... 1) within the next 3 days, 2) within the next week, 3) within the next month, 4) within the next three months and 5) within the next year*.

Probability task

In Study 1, participants completed two probability tasks. The instructions were: *The following questions are not meant as a mathematical test but intended to better understand your intuitions and assessment of probability distributions. You will see jars with coloured balls. A ball is drawn from the jar, its colour is recorded and the ball is put back into the jar. Then, the next item is drawn, the colour noted, and put back. This procedure is repeated three times, resulting in a three-colour-combination.* In Probability Task 1, we showed participants an image of a jar containing 100 balls, 90 of which were blue and 10 yellow, first ordered by color and then an example image of a mixed jar. In a first step, we asked participants which of four color combinations would most likely be sampled in a random order: BBB, BBY, BYY or YYY. Next, participants were asked to estimate the probability of each of the four color combinations, again in random order (*Please indicate the probabilities (0 % to 100 %) for these combinations (order does not matter, so blue-blue-yellow would be the same as blue-yellow-blue and yellow-blue-blue). We are interested in your intuitive answers. Intuitively, how likely is it to draw...*. In Study 2, we changed the instructions in brackets to make it more explicit that the queried color combinations referred exactly to the displayed combinations in the picture: *note that blue-blue-yellow represents drawing a blue ball in the first and second draw and a yellow ball in the third draw; blue-yellow-yellow represents drawing a blue ball in the first draw and a yellow ball in the second and third draw.* Participants were asked to estimate the probability in percent of drawing each of the four color combinations on a slider with values ranging from 0 to 100 (increments of 1 in Study 1 and increments of 0.235 in Study 2). Task 2 in Study 1 was similar to Task 1, only that the constitutive jar contained 100 balls of three different colors: 90 blue, 7 green and 3 yellow balls. Correspondingly, participants rated 10 color combinations.

Statistical methods

Linear mixed models were fitted using the *lmer()* function from the *lme4* package. Analyses were validated using the *robustlmm* package. In all mixed models, participants were included as random effects. R^2 was calculated using the *r.squaredGLMM()* function from the *MuMIn* package, returning marginal effects (relative variance explained by fixed effects) and conditional effects (variance explained by the complete model including fixed and random effects). Predictor variables were z-standardized before performing any regression. Bootstrapped 95% confidence intervals (*CIs*) were obtained using the *confint.merMod()* function from the *lme4* package. β coefficients and σ values were bootstrapped with 10000 simulations per model. Type III ANOVAs using Satterthwaite's method were run on each model to obtain F-statistics and p-values. Logistic regressions were fitted using the *glm()* method with the argument *family = binomial("logit")* and model parameters bootstrapped using the *boot()* function from the *boot* package with 10000 simulations for each test.

Data availability

The human subjects data that support the findings of this study are available in the "Open Science Framework" repository with the identifier 10.17605/OSF.IO/9CRQ6 (https://osf.io/9crq6/?view_only=80f45d9c41de4e5cbd69c11f462441f5).

Code availability

The code that support the findings of this study are available in the "Open Science Framework" repository with the identifier 10.17605/OSF.IO/9CRQ6 (https://osf.io/9crq6/?view_only=80f45d9c41de4e5cbd69c11f462441f5).

References

1. Peterson, C. R. & Beach, L. R. Man as an intuitive statistician. *Psychol. Bull.* **68**, 329–46 (1967).
2. Edwards, W. Conservatism in human information processing. In Kleinmuntz, B. (ed.) *Formal Representation of Human Judgment*, 17–52 (New York: Wiley, 1968).
3. Tversky, A. Assessing uncertainty. *J. Royal Stat. Soc. Ser. B (Methodological)* **36**, 148–159 (1974).
4. Tversky, A. & Kahneman, D. Judgment under uncertainty: Heuristics and biases. *Science* **185**, 1124–1131 (1974).
5. Gigerenzer, G. & Hoffrage, U. How to improve bayesian reasoning without instruction: frequency formats. *Psychol. Rev.* **102**, 684–704 (1995).
6. Gigerenzer, G. & Gaissmaier, W. Heuristic decision making. *Annu. Rev. Psychol.* **62**, 451–482 (2011).
7. Bar-Hillel, M. On the subjective probability of compound events. *Organ. Behav. Hum. Perform.* **9**, 396–406 (1973).
8. Beyth-Marom, R. The subjective probability of conjunctions (1981).
9. Slovic, P. Manipulating the attractiveness of a gamble without changing its expected value. *J. Exp. Psychol.* **79**, 139–145 (1969).
10. Kahneman, D. & Tversky, A. Subjective probability: A judgment of representativeness. *Cogn. Psychol.* **3**, 430–454 (1972).
11. Tversky, A. & Kahneman, D. Extensional versus intuitive reasoning: The conjunction fallacy in probability judgment. *Psychol. Rev.* **90**, 293–315 (1983).
12. Erev, I., Wallsten, T. S. & Budescu, D. V. Simultaneous over-and underconfidence: The role of error in judgment processes. *Psychol. Rev.* **101**, 519–527 (1994).
13. Hilbert, M. Toward a synthesis of cognitive biases: how noisy information processing can bias human decision making. *Psychol. Bull.* **138**, 211–237 (2012).
14. Zhu, J.-Q., Sanborn, A. N. & Chater, N. The bayesian sampler: Generic bayesian inference causes incoherence in human probability judgments. *Psychol. Rev.* **127**, 719–748 (2020).
15. Costello, F. & Watts, P. Surprisingly rational: probability theory plus noise explains biases in judgment. *Psychol. Rev.* **121**, 463–480 (2014).
16. Dolan, R. J. Emotion, cognition, and behavior. *Science* **291**, 1449–1451 (2001).

17. Lerner, J. S. & Keltner, D. Beyond valence: Toward a model of emotion-specific influences on judgement and choice. *Cogn. Emot.* **14**, 473–493 (2000).

18. Tiedens, L. Z. & Linton, S. Judgment under emotional certainty and uncertainty: the effects of specific emotions on information processing. *J. Pers. Soc. Psychol.* **81**, 973–988 (2001).

19. Frijda, N. H., Kuipers, P. & Ter Schure, E. Relations among emotion, appraisal, and emotional action readiness. *J. Pers. Soc. Psychol.* **57**, 212–228 (1989).

20. Frijda, N. H. Emotion, cognitive structure, and action tendency. *Cogn. Emot.* **1**, 115–143 (1987).

21. Smith, C. A. & Ellsworth, P. C. Patterns of cognitive appraisal in emotion. *J. Pers. Soc. Psychol.* **48**, 813–838 (1985).

22. Wright, W. F. & Bower, G. H. Mood effects on subjective probability assessment. *Organ. Behav. Hum. Decis. Process.* **52**, 276–291 (1992).

23. FeldmanHall, O., Glimcher, P., Baker, A. L. & Phelps, E. A. Emotion and decision-making under uncertainty: Physiological arousal predicts increased gambling during ambiguity but not risk. *J. Exp. Psychol. Gen.* **145**, 1255–1262 (2016).

24. Loewenstein, G. & Lerner, J. The role of affect in decision making. 619–642 (2003).

25. Wichary, S., Mata, R. & Rieskamp, J. Probabilistic inferences under emotional stress: how arousal affects decision processes. *J. Behav. Decis. Mak.* **29**, 525–538 (2016).

26. Lerner, J. S. & Keltner, D. Fear, anger, and risk. *J. Pers. Soc. Psychol.* **81**, 146–159 (2001).

27. Clore, G. L., Gasper, K. & Garvin, E. Affect as information. *Handb. Affect. Soc. Cogn.* 121–144 (2001).

28. Schwarz, N. & Bless, H. Happy and mindless, but sad and smart? the impact of affective states on analytic reasoning. In Forgas, J. P. (ed.) *International Series in Experimental Social Psychology. Emotion and Social Judgments*, 55–71 (Pergamon Press, 1991).

29. Schwarz, N. Emotion, cognition, and decision making. *Cogn. Emot.* **14**, 433–440 (2000).

30. Johnson, E. J. & Tversky, A. Affect, generalization, and the perception of risk. *J. Pers. Soc. Psychol.* **45**, 20–31 (1983).

31. Volz, K. G. & Hertwig, R. Emotions and decisions: Beyond conceptual vagueness and the rationality muddle. *Perspectives on Psychol. Sci.* **11**, 101–116 (2016).

32. Kaufman, B. E. Emotional arousal as a source of bounded rationality. *J. Econ. Behav. & Organ.* **38**, 135–144 (1999).

33. Keltner, D. & Gross, J. J. Functional accounts of emotions. *Cogn. & Emot.* **13**, 467–480 (1999).

34. Hanoch, Y. & Vitouch, O. When less is more: Information, emotional arousal and the ecological reframing of the yerkes-dodson law. *Theory & Psychol.* **14**, 427–452 (2004).

35. Teigen, K. H. Variants of subjective probabilities: Concepts, norms, and biases. In Wright, G. & Ayton, P. (eds.) *Subjective Probability*, 211–238 (John Wiley & Sons, 1994).

36. Yerkes, R. M., Dodson, J. D. *et al.* The relation of strength of stimulus to rapidity of habit-formation. *Punishment: Issues Exp.* 27–41 (1908).

37. McGinley, M. J., David, S. V. & McCormick, D. A. Cortical membrane potential signature of optimal states for sensory signal detection. *Neuron* **87**, 179–192 (2015).

38. Schwarz, N. & Clore, G. L. Mood as information: 20 years later. *Psychol. Inq.* **14**, 296–303 (2003).

39. Mehrabian, A. Pleasure-arousal-dominance: A general framework for describing and measuring individual differences in temperament. *Curr. Psychol.* **14**, 261–292 (1996).

40. Bakker, I., Van Der Voordt, T., Vink, P. & De Boon, J. Pleasure, arousal, dominance: Mehrabian and russell revisited. *Curr. Psychol.* **33**, 405–421 (2014).

41. Johnson, S. L., Leedom, L. J. & Muhtadie, L. The dominance behavioral system and psychopathology: evidence from self-report, observational, and biological studies. *Psychol. Bull.* **138**, 692–734 (2012).

42. Eisenberg, P. Factors related to feeling of dominance. *J. Consult. Psychol.* **1**, 89–92 (1937).

43. Jerram, M., Lee, A., Negreira, A. & Gansler, D. The neural correlates of the dominance dimension of emotion. *Psychiatry Res. Neuroimaging* **221**, 135–141 (2014).

44. Foxall, G. Affective responses to consumer situations. *The Int. Rev. Retail. Distribution Consumer Res.* **7**, 191–225 (1997).

45. Russell, J. A. & Mehrabian, A. Evidence for a three-factor theory of emotions. *J. Res. Pers.* **11**, 273–294 (1977).

46. Bradley, M. M. & Lang, P. J. Measuring emotion: the self-assessment manikin and the semantic differential. *J. Behav. Ther. Exp. Psychiatry* **25**, 49–59 (1994).

47. Lang, P. Behavioral treatment and bio-behavioral assessment: Computer applications. *Technol. Mental Heal. Care Deliv. Syst.* 119–137 (1980).

48. Irtel, H. Pxlab: The psychological experiments laboratory [online]. version 2.1.11. (2007). Http://www.pxlab.de, retrieved May 5th 2019.

49. Dasgupta, I., Schulz, E., Tenenbaum, J. B. & Gershman, S. J. A theory of learning to infer. *Psychol. Rev.* **127**, 412–441 (2020).

50. Benjamin, D. J. Errors in probabilistic reasoning and judgment biases. *Handb. Behav. Econ. Appl. Foundations 1* **2**, 69–186 (2019).

51. Schwarz, N. Feelings as information: Implications for affective influences on information processing. *Theor. Mood Cogn. A User's Guideb.* 159–176 (2001).

52. Daniels, K. Affect and information processing. In *The Oxford handbook of organizational decision making* (2008).

53. Kirzinger, A., Kearney, A., Hamel, L. & Brodie, M. Kff health tracking poll - early april 2020: The impact of coronavirus on life in america (2020). Https://www.kff.org/coronavirus-covid-19/report/kff-health-tracking-poll-early-april-2020/, retrieved February 10th 2021.

54. Panchal, N., Kamal, R., Cox, C. & Garfield, R. The implications of covid-19 for mental health and substance use (2021). Https://www.kff.org/coronavirus-covid-19/issue-brief/the-implications-of-covid-19-for-mental-health-and-substance-use/view/footnotes/, retrieved February 10th 2021.

55. Koma, W. *et al.* One in four older adults report anxiety or depression amid the covid-19 pandemic (2020). Https://www.kff.org/medicare/issue-brief/one-in-four-older-adults-report-anxiety-or-depression-amid-the-covid-19-pandemic/, retrieved February 10th 2021.

56. Lerner, J. S., Li, Y., Valdesolo, P. & Kassam, K. S. Emotion and decision making. *Annu. Rev. Psychol.* **66**, 799–823 (2015).

57. Russel, J. A. & Mehrabian, A. Distinguishing anger and anxiety in terms of emotional response factors. *J. Consult. Clin. Psychol.* **42**, 79–83 (1974).

58. Juslin, P., Nilsson, H. & Winman, A. Probability theory, not the very guide of life. *Psychol. Rev.* **116**, 856–974 (2009).

59. Jenny, M., Rieskamp, J. & Nilsson, H. Inferring conjunctive probabilities from noisy samples: Evidence for the configural weighted average model. *J. Exp. Psychol. Learn. Mem. Cogn.* **40**, 203–217 (2014).

60. Talarico, J. M., Berntsen, D. & Rubin, D. C. Positive emotions enhance recall of peripheral details. *Cogn. Emot.* **23**, 380–398 (2009).

61. Yegiyan, N. S. & Yonelinas, A. P. Encoding details: Positive emotion leads to memory broadening. *Cogn. Emot.* **25**, 1255–1262 (2011).

62. Edwards, W., Phillips, L. D., Hays, W. L. & Goodman, B. C. Probabilistic information processing systems: Design and evaluation. *IEEE Transactions on Syst. Sci. Cybern.* **4**, 248–265 (1968).

63. Sundh, J., Zhu, J., Chater, N. & Sanborn, A. N. The mean-variance signature of bayesian probability judgment. (2021).

64. Mills, C. & D′Mello, S. On the validity of the autobiographical emotional memory task for emotion induction. *PLOS ONE* **9**, 1–10 (2014).

Author contributions statement

L.B. conceived the experiments, L.B. and J. D. N. conducted the experiments, L.B. analysed the results, L.B. drafted a first version of the manuscript, L.B, J.D.N. and E.S. composed the final version of the manuscript. All authors reviewed the manuscript.

Additional information

Competing interests: The authors declare no competing interests.