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Prediction That Conflicts With Judgment: The Low Absolute Likelihood Effect

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How do people predict the outcome of an event from a set of possible outcomes? One might expect people to predict whichever outcome they believe to be most likely to arise. However, we document a robust disconnect between what people predict and what they believe to be most likely. This disconnect arises because people consider not only relative likelihood but also absolute likelihood when predicting. If people think that an outcome is both the most likely to arise and has a high absolute likelihood of arising, they regularly predict it to arise. However, if people believe that an outcome is the most likely to arise but has a low absolute likelihood (e.g., it has a 20% chance, and other outcomes have smaller chances), they less often choose it as their prediction, even though they know it is most likely. We find that, when the most likely outcome has a low absolute likelihood, the final outcome feels hard to foresee, which leads people to use arbitrary prediction strategies, such as following a gut feeling or choosing randomly, instead of predicting more logically. We further find that predictions are less likely to depart from the most likely outcome when manipulations encourage people to focus more on relative likelihood and less on the low absolute likelihood. People also exhibit a smaller disconnect when advising others than when predicting for themselves. Thus, contrary to common assumptions, predictions may often systematically depart from likelihood judgments. We discuss implications for research on judgments, predictions, and uncertainty.

Public Significance Statement

When people forecast an uncertain event (e.g., forecasting which team will win the World Cup), they could either state what they think is most likely to happen (which team is most likely to win) or state what they predict to happen (which team they predict will win). Although it seems that these two types of responses would be interchangeable (e.g., if someone thinks France is most likely to win, that person will also predict that they will win), we find that these two responses can be quite different. Specifically, when people think that the most likely outcome is unlikely in an overall, absolute sense (despite still being the most likely outcome), their predictions sometimes depart from what they think is most likely. Thus, predictions diverge from likelihood judgments in certain predictable ways.

Keywords: prediction, likelihood judgment, heuristics, behavioral decision theory

Supplemental materials: https://doi.org/10.1037/xge0001721.supp

People often make predictions about uncertain events that have several possible outcomes. A traveler may need to forecast whether it will be rainy, cloudy, or sunny on their trip. A voter may want to predict the winner in an election. A parent may speculate about which college their child will attend. A basketball fan may want to predict which team will win the title. One might expect people to predict what they believe to be most likely: That is, if a person thinks Kansas is *most likely* to win the college basketball tournament known as March Madness, they would *predict* Kansas to be the winner. Does this statement, albeit intuitive, always reflect behavior? We

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Portions of this research were presented at the annual conference of the Association for Consumer Research (October 2022), the annual conference of the Society of Judgment and Decision Making (November 2022), the annual conference of the Society of Consumer Psychology (March 2024), and the Behavioral Decision Research in Management conference (June 2024). The authors have no known conflicts of interest to disclose.

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suggest that it does not, and we document a robust disconnect between prediction and likelihood judgment.

Predictions Versus Likelihood Judgments

Extensive research has shown that likelihood judgments and predictions can be biased. Much early research focused on how such judgments and predictions diverge from formal probability models. One well-known finding is that people often rely on shortcuts or heuristics, rather than a formal calculus, to make judgments and predictions (e.g., Kahneman et al., 1982; Tversky & Kahneman, 1974). For example, people may predict by considering the degree to which the key characteristics of the available evidence resemble a possible outcome while underweighting the objective probability of that outcome (Kahneman & Tversky, 1973). Judgments and predictions have also been shown to be influenced by a host of factors including, but not limited to, affect (Fischhoff et al., 1978; Loewenstein et al., 2001; Slovic, 1987; Slovic et al., 2004, 2007), optimism (Krizan et al., 2010; Massey et al., 2011; Weinstein, 1980), past history (e.g., Bar-Hillel & Wagenaar, 1991; Gilovich et al., 1985; Jarvik, 1951), and intuitions and confidence (Simmons & Nelson, 2006).

Although prior research on judgment and prediction has taken many different directions and explored many potential biasing factors, one thing that unites this research is that people's predictions are generally thought to follow from, and be consistent with, their likelihood judgments. That is, if a person thinks, for whatever reason, that heads is more likely to come up than tails on an upcoming coin flip, that person will also predict that heads will come up. As Howell and Burnett (1978) noted, "[n]aturally we assume that his prediction will reflect the event to which he ascribes the greatest likeliness at the moment" (p. 52).

This assumption is very intuitive and often true. Although little research has directly examined whether predictions and subjective likelihood judgments correspond—probably because such connection usually seems obvious—some work happens to provide evidence that supports this correspondence. For example, Simmons and Massey (2012) showed that football fans who optimistically predicted their preferred team as the winner indeed estimated that their team had a higher likelihood of winning the game than their opponent, even when their preferred team was objectively inferior to the other.

In other articles, researchers quite reasonably observe predictions as a way of gauging likelihood judgments (and vice versa), indicating a tacit assumption that the two likely often correspond. For example, in demonstrating the representativeness heuristic, Kahneman and Tversky often treated predictions and likelihood judgments as interchangeable measures. In a classic study, they measured people's predictions of a graduate student's field of study by asking participants to rank the possible fields in order of their likelihoods (Kahneman & Tversky, 1973). In another study, they illustrated a bias in subjective probabilities by measuring people's predictions about which program a class of students were from (Kahneman & Tversky, 1972). They noted, "A person bets on team A rather than on team B because he believes that team A is more likely to win" (Tversky & Kahneman, 1974, p. 1130), and their view of the relationship between likelihood (or frequency) and prediction was, "[i]n category prediction, one predicts the most frequent category" (Kahneman & Tversky, 1973, p. 243).[1]

These views are quite reasonable, but it is not always the case that people predict that their perceived most likely outcome will arise. Some anomalies have been identified when people make multiple predictions. One such case is the phenomenon of probability matching. When predicting for a class of events that each have the same outcome probabilities, people tend to broadly match their predictions to the probabilities, sometimes disregarding what is most likely for a single event. For example, when predicting a repeated drawing that has a 70% chance of yielding red on each draw and a 30% chance of yielding black, people may predict red on 70% of the trials and black on 30% even when they are clearly aware that red is always more likely (e.g., Koehler & James, 2009; Neimark & Shuford, 1959; for an extensive review, see Vulkan, 2000). Another case involves sequential predictions, with the finding that people are more likely to predict an improbable outcome (e.g., an underdog winning a match) for predictions that they make later versus earlier in a sequence (Silverman & Barnea, 2024).

For people making a single prediction, desirability has been shown to produce a discrepancy between what people predict and what they believe to be more likely to arise. Making an outcome more desirable (e.g., associating it with a monetary payoff) biases people's predictions toward that outcome (e.g., Marks, 1951), but likelihood judgments tend to be less affected by desirability (Park et al., 2023; Windschitl et al., 2010; see also Bar-hillel & Budescu, 1995).

Although not strictly related to prediction, research has also identified a disconnect between likelihood judgment and choice that arises when intuitive perceptions conflict with logical analysis. For example, when people try to draw a red bean from a bowl of beans, some people prefer to draw from a bowl of 100 beans that contains nine red beans over a bowl of 10 beans that contains one red bean. Participants report feeling that the bowl with nine red beans gives them more ways to win, even though they report knowing that the likelihood of winning is greater in the bowl with one red bean (ratio bias; Denes-Raj & Epstein, 1994). Such a finding suggests that perceptions of what will happen may diverge from pure likelihood assessments.

Relative Likelihood Versus Absolute Likelihood

In this article, we investigate a different, and potentially more pervasive, factor that causes prediction and likelihood to diverge: the sense that even the most likely outcome is nevertheless not very likely in an absolute sense. When one predicts from discrete options, how likely an outcome is to arise compared to other alternatives (i.e., relative likelihood) is generally more relevant than how likely it is to arise in an absolute sense (i.e., absolute likelihood). If one's goal is to maximize predictive accuracy, one should consider the relative likelihoods of the possible outcomes and choose the outcome that is more likely to arise than any other alternative, regardless of whether that outcome has a high or low likelihood in absolute terms.

However, predictions may not always follow this prescription. Unlike likelihood judgment, prediction involves all-or-none

[1] As described by Kahneman and Tversky (1973), "category prediction" is any prediction that requires people to predict an uncertain event that has several possible nominal outcomes, like predicting the outcome of a coin toss, the result of a die roll, or the winner of a tournament. The current article focuses exclusively on category prediction, so for simplicity, we use the term "prediction."

specification of future events, and such a task may feel quite different from judging likelihood (Howell & Burnett, 1978). Instead of estimating which outcome is most likely to arise, predictors must indicate which outcome will indeed arise. Any possible outcome can arise, which adds ambiguity to whether a prediction is right or wrong a priori. Thus, researchers have speculated that people may, at times, make predictions that are inconsistent with their likelihood judgments because this ambiguity could make people feel free to make somewhat arbitrary predictions that are decoupled from those judgments (Howell & Burnett, 1978; Park et al., 2023; Windschitl et al., 2010).

These ideas leave an unanswered question: When will such inconsistencies between prediction and likelihood judgment be most likely to occur? We argue that one key factor is the absolute likelihood of the most likely outcome. Whereas relative likelihood refers to how an outcome's likelihood compares to the likelihood of other outcomes (e.g., how does the likelihood of Kansas winning compare to the likelihood of other teams winning), absolute likelihood refers to how likely an outcome is without such comparisons (e.g., how likely is Kansas to win). When the most likely outcome has a high absolute likelihood and therefore feels very likely to arise, ambiguity surrounding the final outcome is largely reduced: The most likely outcome is highly likely in both a relative and an absolute sense, and people may easily foresee the occurrence of that outcome. Thus, we expect that people will regularly predict that the most likely outcome will arise when it has a high absolute likelihood.

However, there may be times when even the most likely outcome's absolute likelihood is low (e.g., the most likely outcome has a 10% chance of arising, and all other possible outcomes have lower chances). In such cases, even though the most likely outcome may be clear, no option may seem particularly likely to arise, and the eventual outcome may feel difficult to foresee. This may therefore pose substantial ambiguity as to whether a prediction is right or wrong a priori. If predictions may be sensitive to distorting, nonlogical influences due to the inherent ambiguity of predictions (Howell & Burnett, 1978), they may be especially susceptible to such distorting influences in these situations when the most likely outcome's absolute likelihood is low.

Thus, we predict that, when the most likely outcome has a low absolute likelihood, the final outcome will feel relatively difficult to foresee. People may have thoughts along the lines of "anything can happen" and may consequently feel free to predict arbitrarily, by which we mean predicting via an explicitly nonlogical method, such as choosing randomly, going with a gut feeling, choosing a desired outcome (e.g., a favorite team or a lucky number), or simply guessing. People might also start to pursue other goals besides maximizing predictive accuracy. For example, some might predict a less likely outcome because it would be fun if it was right, whereas others might select a particular outcome to feel unique. Such a process may lead predictions to depart from what people perceive or know to be the most likely outcome.

To make this more concrete, consider again the person who thinks Kansas is most likely to win the championship among all 68 teams in March Madness. If they think Kansas has an 80% chance of winning the title (absolute likelihood of the most likely outcome is high), they can easily predict that Kansas will be the champion: Their prediction will be the same as the team they think is most likely to win.

However, if they think Kansas, albeit the most likely, only has a 10% chance of winning (absolute likelihood of the most likely outcome is low), they might feel that Kansas is not, overall, particularly likely to win. After all, from their point of view, there is a 90% chance that some other team might win. The substantial uncertainty posed by the 90% chance of any other team winning could make the winner feel hard to foresee. This sense of low foreseeability may license people to predict arbitrarily, in a manner decoupled from their perception of which team is most likely to win: They may rely on a hunch, a guess, or a team they like. Thus, although they still may believe that Kansas is more likely to win than other teams, because that likelihood of winning seems rather low, they may predict something other than Kansas.

We thus predict that likelihood judgments will correspond to predictions as long as the most likely outcome also seems likely overall to people, but that predictions will be more likely to depart from likelihood judgments when the most likely outcome seems unlikely overall—even though the perception of which outcome is most likely remains intact. In other words, when the absolute likelihood of the most likely outcome is low, we predict that there will be a gap between how many participants identify that outcome as most likely and how many predict it. We suggest that this gap is driven (a) by outcomes seeming difficult to foresee when the most likely outcome is unlikely in an absolute sense and (b) by this low foreseeability leading people to predict arbitrarily (e.g., by relying on strategies apart from conventional logic). Because we anticipate that people are generally sensitive to absolute likelihood in addition to relative likelihood, we also suggest that increasing the focus on relative likelihood or decreasing the focus on the low absolute likelihood will reduce this gap (i.e., will cause predictions to align with likelihood judgments).

This article thus examines how predictions and likelihood judgments may diverge when the absolute likelihood of the most likely outcome is low. It contributes to research on judgment and decision making by showing that probability judgments and predictions cannot be assumed to be the same. While some important research has indeed shown that predictions and probability judgments may diverge, that research has generally focused on relatively specialized circumstances (e.g., probability matching; Koehler & James, 2009; optimism; Park et al., 2023). Here, we identify a factor that is arguably more pervasive—low absolute likelihood—and show how it can distort predictions.

Study Overview

We begin by showing that people's predictions and their perceived most likely outcomes are largely consistent when the most likely outcome is likely to arise but tend to diverge when the most likely outcome is unlikely to arise. We show that this gap between most likely and predicted outcomes emerges even when participants are incentivized to make accurate predictions, even when most-likely judgments and predictions are made within moments of each other, and even for predictions of real-life events (Studies 1 through 5).

Studies 6a and 6b show that, when the most likely outcome is overall unlikely, people find the final outcome to be less foreseeable and in turn acknowledge choosing randomly and arbitrarily. Studies 7 through 8 show that emphasizing the relative likelihood of the most likely outcome or reducing the focus on the low absolute likelihood of that outcome reduces the gap between likelihood judgments and predictions. Finally, Study 9 identifies a boundary of the current effects: The gap between likelihood judgments and predictions is much smaller when people advise others than when they predict for themselves, suggesting that people may find it less appropriate to predict arbitrarily when advising others. The research was approved by the institutional review board at the authors' institution.

Transparency and Openness

All studies are preregistered. All preregistration documents, study materials, raw data, and code can be found on ResearchBox at https://researchbox.org/3083. Preregistration links for each study can be also found in the method section of that study. In all studies, we report all preregistered analyses, measures, manipulations, conditions, and exclusion criteria. Occasionally, a preregistered analysis is not central to our main argument, and so we put it in the Supplemental Materials and note it in the main text. We also describe five additional studies in the Supplemental Materials.

Study 1: Initial Demonstration

Study 1 examines people's predictions and likelihood judgments in a simple game. The game has an obvious most likely outcome, but we manipulate that outcome's absolute likelihood to be high versus low. We also manipulate whether we ask participants to identify the most likely outcome or to predict which outcome will arise. We predict that participants will easily identify the most likely outcome regardless of whether its absolute likelihood is low or high. However, we predict that absolute likelihood will matter for predictions. When the most likely outcome has a high absolute likelihood, we predict that participants will regularly predict that it will obtain, just like they will regularly recognize it as most likely. However, when the most likely outcome has a low absolute likelihood, we predict that participants will be less likely to choose it as their prediction, even though they will still have no trouble identifying it as most likely.

Prior research suggests that outcomes that are considered "unlikely" usually have a probability around 20%–30%, whereas those considered "likely" generally have a probability above 50%, with an average probability around 70% (Budescu & Wallsten, 1995; Clark, 1990; Sirota & Juanchich, 2015; Theil, 2002). Thus, in this and most of the following studies, we manipulate the most likely outcome to be unlikely or likely by setting its likelihood to approximately 20% or 70%, respectively.[2]

Method

Participants and Design

We preregistered (https://aspredicted.org/nbmd-2nk2.pdf) to recruit 600 participants on Amazon Mechanical Turk (MTurk). We received 601 completed responses. Participants were randomly assigned to one cell of a 2 (Likelihood of the Most Likely Outcome: High vs. Low) × 2 (Response: Identify the Most Likely Outcome vs. Predict the Outcome) between-subjects design. Thirty-seven of the 601 participants did not pass an attention check (described below) and were excluded (as preregistered), leaving a final sample of 564 (M_{age} = 40.3 years; 52.3% female, 45.9% male, 1.6% nonbinary, and 0.2% preferring not to say). For this and following studies, we report exclusions by condition in Supplemental Table S1.

Procedure

During an online session, participants played a computerized game. Each participant saw a set of nine numbered balls on the screen and could click to randomly draw a ball from the set. As illustrated in Figure 1, participants saw one of two sets of balls: In the low-chance set, two balls were labeled "1," and the other seven balls were labeled a unique number from "2" to "8." In the high-chance set, six balls were labeled "1," and the remaining three balls were labeled "2" to "4." Although 1 was the most likely number to be drawn from both sets, 1 had a low chance (2/9) of being drawn from the former set and a high chance (6/9) of being drawn from the latter set. Before drawing a ball, participants responded in one of two ways: They either *identified* the most likely outcome ("Which number are you most likely to draw?") or *predicted* which number they would draw ("Which number do you predict you will draw?"). Predictors also read that they would win $1.00 if they successfully predicted the number they drew. Then, participants drew a ball and observed the outcome. At the end, they answered an attention check that asked them to identify how many balls were marked "1."

Results and Discussion

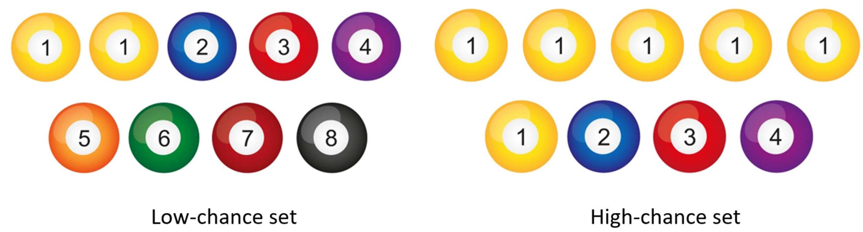
Most participants correctly identified 1 as most likely, regardless of whether the likelihood of drawing a 1 was low (92.6%) or high (96.7%), $\chi^2(1) = 1.62$, $p = .203$. However, predictions were sensitive to likelihood, even though participants were incentivized for correct predictions. Participants were less likely to predict 1 when the likelihood of drawing a 1 was low (63.3%) versus high (92.4%), $\chi^2(1) = 31.82$, $p < .001$; see Figure 2.

Viewed differently, when there was a high chance of drawing a 1, the percentage identifying 1 as the most likely (96.7%) was not reliably different from the percentage predicting 1 (92.4%), $\chi^2(1) = 1.74$, $p = .188$, suggesting a close correspondence between what participants judged most likely and what they predicted. However, when there was a low chance of drawing a 1, there was a gap between the percentage identifying 1 as the most likely (92.6%) and the percentage predicting 1 (63.3%), $\chi^2(1) = 32.84$, $p < .001$. This most-likely versus prediction gap reveals that participants tended to predict a different, less likely number even when they knew that 1 was most likely to be drawn. Supplemental Table S2 shows the full distribution of responses in each condition. As seen in the table, there is not a clear regularity in which number people predict when they do not predict 1; Studies 6a and 6b return to the issue of what governs people's predictions in these cases. We replicated these results with a different number (3, instead of 1) as the most likely outcome in Supplemental Study S1.

Thus, when people predict from a set of possible outcomes, they do not always predict the most likely outcome, despite recognizing it as most likely. When people can recognize a most likely outcome and it feels likely in an absolute sense, they predict with ease that it will arise. However, when the most likely outcome feels unlikely in

[2] Study 5, as well as Supplemental Study S3, allows this likelihood to vary naturally across a wide range. Supplemental Study S5 systematically manipulates this likelihood to vary from 10% to 90%.

Figure 1
Study 1 Materials



Note. See the online article for the color version of this figure.

an absolute sense, people are less likely to choose it as their prediction—even though they can still easily identify which number is most likely and stand to gain money from making a correct prediction.

Study 2: Equal Numbers of Options

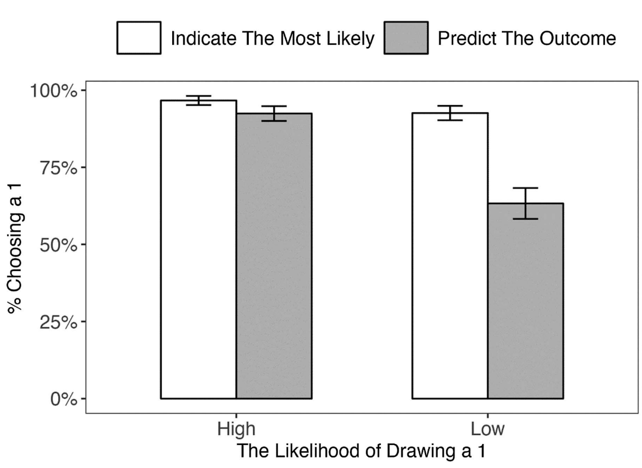
In Study 1, the low-chance set had more possible outcomes (1 through 8) than the high-chance set (1 through 4). Thus, participants had more options to choose from when selecting from the low-chance set than from the high-chance set: is this why people were more likely to deviate from the optimal prediction of 1 in the low-chance set? After all, even a person choosing randomly would be less likely to correctly predict 1 from the low-chance set that had more numbers to choose from. Such an account would not explain why only predictions, and not most-likely judgments, were affected by the high-chance versus low-chance manipulation, but nevertheless, to address this possibility, we controlled for the number of possible outcomes in Study 2.

Method

Participants

As preregistered, we recruited 600 participants from Prolific (https://aspredicted.org/5vkw-4f5f.pdf). Twenty-four of them did not pass the attention check, leaving us with 576 observations (M_{age} = 36.7 years; 52.3% female, 45.1% male, 2.4% nonbinary, and 0.2% preferring not to say). As in Study 1, participants were randomly assigned to one cell of a 2 (Likelihood of the Most Likely Outcome: High vs. Low) × 2 (Response: Identify the Most Likely Outcome vs. Predict the Outcome) between-subjects design.

Figure 2
Study 1 Results



Note. *SE* = standard error.

Procedure

During an online session, participant saw one of two sets of 18 numbered balls on the screen, as illustrated in Figure 3. In the low-chance set, the number 1 appeared on four balls, whereas the numbers 2 through 8 appeared on two balls each. In the high-chance set, the number 1 appeared on 11 balls, whereas the numbers 2 through 8 appeared on one ball each. Although 1 was the most likely number to be drawn from both sets, 1 had a low chance (4/18) of being drawn from the low-chance set and a high chance (11/18) of being drawn from the high-chance set. Unlike in Study 1, both sets had the same set of possible outcomes so that when participants responded, they always picked a number from 1 to 8. Before drawing a ball, participants either identified the most likely outcome or predicted which number they would draw. Then, participants clicked to randomly select a ball and observed the outcome. At the end, they answered an attention check that asked them to identify how many balls were marked “1.”

Results and Discussion

Nearly everyone correctly identified 1 as the most likely number, regardless of whether they saw the low-chance set (91.6%) or the high-chance set (96.3%), $\chi^2(1) = 1.93$, $p = .164$. However, predictions were sensitive to likelihood. Participants were less likely to predict 1 when the likelihood of drawing a 1 was low (70.9%) versus high (94.0%), $\chi^2(1) = 25.53$, $p < .001$.

Viewed differently, with the high-chance set, the percentage identifying 1 as the most likely (96.3%) was not reliably different from the percentage predicting 1 (94.0%), $\chi^2(1) = .37$, $p = .543$. However, with the low-chance set, there was a gap between the percentage identifying 1 as the most likely (91.6%) and the percentage predicting 1 (70.9%), $\chi^2(1) = 19.74$, $p < .001$. Supplemental Table S2 shows the full response distribution.

Study 2 replicated the patterns observed in Study 1 while keeping the possible outcomes identical across conditions. The correspondence between predictions and most likely outcomes is

Figure 3
Study 2 Materials

Note. See the online article for the color version of this figure.

affected by the absolute likelihood of the most likely outcome–even if people predict from the same of possible outcomes.

Study 3: A Within-Subjects Design

In the first two studies, we measured people's predictions and likelihood judgments between subjects. Study 3 examines these responses within subjects. This design allows us to see if the low absolute likelihood effect persists even when participants give their prediction immediately following their most-likely response (and vice versa), amounting to a fairly stringent test of whether participants truly mean to predict something different from what they think is most likely. This design also allows us to examine an alternative explanation: It is possible that, in the low-likelihood conditions, participants did not assess the likelihoods of the possible outcomes before predicting but were nevertheless able to identify the most likely outcome when asked. That is, rather than predicting contrary to their likelihood judgments, perhaps they simply did not make likelihood judgments when predicting. A within-subjects design addresses this question by prompting some participants to first identify the most likely outcome before making a prediction.

Method

Participants

As preregistered (https://aspredicted.org/kbz8-xd2w.pdf), we recruited 300 MTurk participants.[3] None were excluded from the analysis.

Procedure

Participants considered a set of nine (virtual) balls. Two balls were marked "1" and seven were marked "2" to "8." (We only used the low-chance set because that is where we observed the most-likely vs. prediction gap in Studies 1 and 2.) Before randomly drawing a ball, participants both identified which number they were most likely to draw and predicted which number they would draw. Between these two questions, we told participants, "Your answer here can be the same as, or different from, the answer to the previous question." The order of the two tasks was counterbalanced.

Results and Discussion

As preregistered, we first examined participants' responses to their first question for a between-subjects comparison. We replicated the low absolute likelihood effect. Of those who first identified which number was most likely to be drawn, almost all (93.3%) correctly identified 1, but of those who first made a prediction, only 61.3% predicted 1, $\chi^2(1) = 42.01$, $p < .001$.

Next, we examined participants' responses to both questions for a within-subjects comparison. The gap persisted within participants. Of the 300 participants, most (88.0%) identified 1 as most likely, but only 59.7% predicted that they would draw a 1, $\chi^2(1) = 60.87$, $p < .001$. This gap appeared in both question orders. When participants first predicted, 61.3% of them predicted a 1 but subsequently many more of them (82.7%) recognized 1 as most likely, $\chi^2(1) = 15.89$, $p < .001$. Perhaps more notably, when participants first identified the most likely number, almost all of them (93.3%) identified 1, but then only 58.0% predicted 1 immediately thereafter, $\chi^2(1) = 48.95$, $p < .001$. Thus, many people still did not predict the most likely number even when they had just recognized and explicitly stated that number. Predicting after identifying the most likely number did not increase the percentage predicting a 1, $P_{\text{prediction second}} = 58.0\%$ versus $P_{\text{prediction first}} = 61.3\%$, $\chi^2(1) = .22$, $p = .638$, even though participants were more likely to identify 1 as most likely before versus after prediction, $P_{\text{prediction second}} = 93.3\%$ versus $P_{\text{prediction first}} = 82.7\%$, $\chi^2(1) = 7.10$, $p = .008$. Supplemental Table S2 shows the full response distribution. We also replicated these results even when participants were given a monetary incentive for accurate prediction and were explicitly reminded of their indicated most likely number before their predictions (see Supplemental Study S2).

Study 3 examines whether people's predictions still diverge from the most likely outcome even when the responses are given within moments of each other. We find that, indeed, this divergence still arises, suggesting that it does not arise because people have not thought about the most likely outcome before they make a prediction.

[3] We did not collect demographic data in this study. The CloudResearch platform provides overall information about gender (51% female and 49% male) and birth decade (1% from the 1940s, 6% from the 1950s, 12% from the 1960s, 16% from the 1970s, 37% from the 1980s, 25% from the 1990s, 2% from the 2000s, and 1% unknown).

Studies 4a and 4b: Everyday Contexts

Studies 4a and 4b seek to replicate the low absolute likelihood effect in contexts beyond ball-drawing games to show how it might arise in daily life. Study 4a involves a college choice, and Study 4b features a soccer tournament.

Study 4a

Method

Participants

As preregistered (https://aspredicted.org/j8sp-kd3b.pdf), we recruited 600 participants from Prolific. Twenty did not pass the attention check, leaving us with 580 observations (M_{age} = 38.6 years; 49.7% female, 47.6% male, 1.9% nonbinary, and 0.9% preferring not to say). Participants were randomly assigned to one cell of a 2 (Likelihood: High vs. Low) × 2 (Task: Identify the Most Likely Outcome vs. Predict the Outcome) between-subjects design.

Procedure

Participants imagined that a high school student, Emily, was accepted at six universities. Participants saw the likelihood that Emily would attend each university. They saw one of two sets of likelihoods, depending on which condition they were assigned to (see Table 1). In all conditions, Emily was most likely to attend the University of Michigan. The likelihood of attending Michigan was 70% in the high-likelihood conditions but was much lower (25%) in the low-likelihood conditions. Participants either indicated which university Emily was most likely to attend or predicted which university she would attend. Finally, as an attention check, participants identified which of three universities admitted Emily.

Results and Discussion

As preregistered, we examined the gap between people's predicted universities and their indicated most likely universities when Michigan had a low, versus high, likelihood of being chosen by Emily. When Emily was 70% likely to attend Michigan, nearly everyone (95.7%) recognized that she was most likely to attend Michigan, and nearly everyone (91.0%) predicted that she would attend Michigan, $\chi^2(1) = 1.81$, $p = .178$. However, when Emily was only 25% likely to attend Michigan, most people (89.0%) still recognized that Emily was most likely to attend Michigan, but only 64.0% predicted that Emily would eventually go to Michigan, $\chi^2(1) = 24.03$, $p < .001$. The percentage indicating Michigan as most likely did not reliably differ when Michigan had a low versus high likelihood, $P_{low} = 89.0\%$ versus $P_{high} = 95.7\%$, $\chi^2(1) = 3.66$, $p = .056$, though the difference was marginal, but the percentage predicting Michigan was notably and significantly lower when Michigan had a low likelihood, $P_{low} = 64.0\%$ versus $P_{high} = 91.0\%$, $\chi^2(1) = 29.18$, $p < .001$. Study 4b thus shows the low absolute likelihood effect in a more natural setting than ball-drawing.

Study 4b

Method

Participants

As preregistered (https://aspredicted.org/gm5x-nprk.pdf), we recruited 600 participants from Prolific. Nineteen did not pass the attention check, leaving us with 581 observations (M_{age} = 36.9 years; 52.2% female, 44.4% male, 3.3% nonbinary, and 0.2% preferring not to say). Participants were randomly assigned to one cell of a 2 (Likelihood: High vs. Low) × 2 (Task: Identify the Most Likely Outcome vs. Predict the Outcome) between-subjects design.

Procedure

Participants imagined that an interscholastic soccer tournament was entering the quarter finals with eight middle-school soccer teams. Participants were presented with the likelihood of each team winning the title. They saw one of two sets of likelihoods, depending on which condition they were assigned to (see Table 2). In the high-likelihood conditions, the Nova Nomads were most likely to win the title with a 72% likelihood. In the low-likelihood conditions, the Nova Nomads were still the most likely winner but with only a 22% likelihood. Participants were asked either, "Which team do you think is most likely to win the title?" or "Which team do you predict to win the title?" Finally, as an attention check, they identified which of three teams was in the tournament.

Results and Discussion

As preregistered, we examined the gap between people's predicted title winners and their perceived most likely title winners when the most likely team had a low, versus high, likelihood of winning. When the Nova Nomads were 72% likely to win the title, nearly everyone (98.7%) thought that they were the most likely title winner, and nearly everyone (99.3%) predicted that they would win,

Table 1
Emily's Likelihood of Attending Each University in Study 4a

	Likelihood of attending	
University	Low-likelihood condition	High-likelihood condition
University of Georgia	10%	3%
San Francisco State University	20%	10%
University of Michigan	25%	70%
University of California, San Diego	20%	10%
Colorado State University	15%	5%
Rensselaer Polytechnic Institute	10%	2%

Table 2
Each Team's Likelihood of Winning the Title in Study 4b

Team	Likelihood of winning the title	
	Low-likelihood condition	High-likelihood condition
Ninjas, Pennsylvania	10%	4%
Blue Bulls, New York	18%	5%
Nova Nomads, New York	22%	72%
Techno Tigers, Connecticut	18%	5%
Tornados, Connecticut	12%	5%
Owls, New York	10%	4%
Eagles, Pennsylvania	5%	3%
Grey Wolves, Connecticut	5%	2%

$\chi^2(1) < .001$, $p > .999$. However, when the Nova Nomads were only 22% likely to win the title, although most people (95.0%) still believed that they were most likely to win, only 79.7% predicted that they would win, $\chi^2(1) = 13.65$, $p < .001$. The percentage indicating Nova as the most likely title winner did not reliably differ when the team had a low versus high likelihood, $P_{\text{low}} = 95.0\%$ versus $P_{\text{high}} = 98.7\%$, $\chi^2(1) = 2.25$, $p = .133$, but the percentage predicting Nova to win was significantly lower when the team had a low likelihood, $P_{\text{low}} = 79.7\%$ versus $P_{\text{high}} = 99.3\%$, $\chi^2(1) = 26.44$, $p < .001$. Thus, we again find the low absolute likelihood effect in a more natural setting.

Study 5: March Madness

Our studies thus far have provided consistent experimental evidence for the disconnect between predictions and likelihood judgments: When a most likely outcome is unlikely to arise, people may be able to easily identify it as most likely, but they are less likely to choose it as their prediction, at least partially disregarding their beliefs about it being most likely. In Study 5, we seek further evidence from predictions of a real-life event: the 2022 National Collegiate Athletic Association Division I men's basketball tournament (or March Madness).

Before the 2022 March Madness quarterfinals started, we collected people's perceived most likely title winner, their incentivized predictions of the winner, and their subjective likelihood of each team winning the title in absolute terms. We examine how each person's absolute likelihood assessment of their own most likely team winning relates to their tendency to predict that team to win. One might expect that people will predict their own most likely team as the winner regardless of the subjective absolute likelihood of that team winning. However, we suggest that people will be less likely to predict their own most likely team as the winner when they perceive that this team has a lower, rather than higher, absolute chance of winning.

Method

Participants

The final eight teams in March Madness were decided on March 25, 2022. On March 26 at 6:09 p.m. Eastern, those teams would begin to compete for the final four positions. We preregistered to collect 600 responses on MTurk on March 26 and to stop data collection before 6:09 p.m. even if we did not reach 600 responses (https://aspredicted.org/n4s3-ytdb.pdf). We ended up obtaining 602 responses by 3:53 p.m. Eastern on March 26 ($M_{\text{age}} = 42.5$ years; 45.2% female, 53.8% male, 0.3% selecting "other," and 0.5% preferring not to say).

Procedure

Participants answered three questions in one of two orders. In one order, they first indicated which of the final eight teams was most likely to win the title. On the next screen, they estimated each team's likelihood of winning the title (as a percentage; each participant gave eight percentages that were required to sum to 100%). On the third screen, participants predicted which of the eight teams would win the title and were told that they would win $2.00 if their prediction was correct. In the other order, participants first made an incentivized prediction and then indicated the most likely winner before rating each team's likelihood. At the end of the survey, participants indicated whether they followed college basketball and how frequently they watched college basketball games on a scale from 0 (*never*) to 10 (*very frequently*). These questions were preregistered as exploratory. Controlling for these measures did not affect any of our results, so we do not discuss them further.

Results and Discussion

The Most Likely Winner

There was a possibility for people to be inconsistent when identifying the most likely winner. Participants both directly indicated the most likely winner and estimated the percentage likelihood of each team winning the title. This latter estimate could also reveal beliefs about the most likely winner. Most participants (514 of 602) were consistent between their directly indicated most likely winner and their most likely winner as revealed through percentage likelihoods. We focus on these 514 participants in the analyses below. We also report full-sample analyses, all of which yield the same conclusions, in the Supplemental Materials.

Main Analyses

Participants' estimated likelihoods of their most likely winners ranged from 13% to 100% ($M = 38.2\%$, $SD = 18.6\%$). We created a dependent variable that equaled 1 if a participant's prediction matched their most likely winner and 0 if it did not. We ran a logistic regression regressing this dependent variable on people's estimated reported percentage likelihood of how likely the most likely team was to win, question order (1 = participants first indicated the most likely winner, −1 = participants predicted first), and their interaction.

As predicted, predictions were sensitive to their estimated likelihood of the most likely winner: Participants were less likely to predict their own most likely team when they reported the absolute likelihood of that team winning to be lower ($\beta = .031$, $SE = .008$, $p < .001$). This effect was not qualified by question order, as the Likelihood × Order interaction was not significant ($\beta = -.021$, $SE = .017$, $p = .210$). There was an overall main effect of order that is not directly relevant to our predictions: Participants were more likely to predict their own most likely team to win when they first indicated the most likely team than when they first predicted ($\beta = 1.00$, $SE = .298$, $p < .001$).

Thus, people's predictions are more likely to diverge from their own perceived most likely winner when they perceive that their most likely winner has a lower absolute chance of winning. In the Supplemental Materials, we describe a dichotomous analysis that reaches the same conclusion, and we also report a study (Supplemental Study S3) that replicates these findings with predictions of a National Basketball Association championship.

Study 5 extends our effect to a real-world situation. When people predict a sports championship, they are more likely to disregard their beliefs about which team is likely to win, and to predict a different team as the winner, when they feel that the most likely winner has a lower chance of winning in absolute terms. Of course, this study is correlational, so the results are not free of confounds. Nevertheless, it provides strong correlational evidence for the discrepancy between likelihood judgment and prediction in an ecologically valid setting. People are more apt to make predictions that conflict with what they know to be most likely in specific circumstances, namely, when what is most likely does not appear likely in an absolute sense.

Studies 6a and 6b: Why Do Predictions and Likelihood Estimates Diverge?

We have shown consistent evidence that people tend to predict contrary to what they know to be most likely when the most likely outcome is unlikely to happen in an absolute sense. But why do people do this? We have suggested that the low absolute likelihood effect may arise because, in such situations, the final outcome seems hard to foresee, which may in turn license people to predict in a less logical and more arbitrary fashion, such as by picking a favorite number, picking a lucky number, or just making a pure guess. Studies 6a and 6b investigate this process, beginning in Study 6a by simply asking participants why they predicted something different from their professed most likely outcome.

Study 6a: Free Responses

In Study 6a, people give both a most-likely assessment and a prediction. We invite those who give inconsistent responses to the two questions to tell us why their responses diverge. We examine participants' responses to give us some insight into the low absolute likelihood effect.

Method

Participants

As preregistered (https://aspredicted.org/hnx5-prfj.pdf), we recruited 500 participants from Prolific. Eleven did not pass the attention check, leaving a final sample of 489 ($M_{age} = 36.3$ years; 47.4% female, 49.7% male, and 2.7% selecting "other").

Procedure

Participants saw the low-chance set of balls (Figure 1). Before drawing a ball, they first indicated the most likely number and then predicted which number they would draw. If a participant indicated 1 as most likely but did not predict 1, we then asked them, "What was your reasoning for predicting that you would get [predicted number] instead of a 1?" Participants who gave consistent most-likely and prediction responses or who did not indicate 1 as most likely skipped this open-ended question.

We next asked participants to code their responses in the following way: Each participant reviewed their response and then reported whether it referred to each of the six reasons listed in Table 3, by responding "yes" or "no." The reasons were presented in a randomized order. Participants could answer "yes" or "no" to as many reasons as they felt were applicable to them.

The six reasons shown in Table 3 reflect our hypotheses about why the low absolute likelihood effect arises. The first reason refers to the sense that even the most likely outcome is unlikely to arise. The second and third reasons refer to the perceived low foreseeability of the outcome. The fourth through sixth reasons refer to participants predicting arbitrarily in various ways, such as picking a liked number or a lucky number or going with a gut feeling.

At the end of the survey, all participants answered an attention check that asked them to recall how many balls were marked "1."

Results and Discussion

Predictions

We replicated the most-likely versus prediction gap. Most participants (90.2%) indicated that 1 was most likely to be drawn, but only 63.6% of them predicted a 1, $\chi^2(1) = 95.76$, $p < .001$.

Table 3
Study 6a Self-Coding Results

Reason	% Yes
The likelihood of drawing a 1 was small overall and/or 1 was overall unlikely to be drawn.	51.7%
The drawing is random and anything could happen.	80.7%
The outcome is hard to predict or know in advance.	68.3%
I picked a number I just liked for some reason, such as my lucky number, my birthday, my favorite number, and so on.	40.7%
I guessed or picked a number at random.	66.2%
I went with my gut feeling.	71.7%

Note. The "% Yes" column records the percentage of the total participants who indicated that their response referred to the corresponding reason.

Free Responses

One hundred forty-five participants indicated 1 as most likely but then predicted another number. They explained their thought processes in the subsequent free response question. Their explanations were generally consistent with our proposed process. They often acknowledged that their predictions were influenced by the low likelihood of drawing a 1. For example, one said:

> Although there are two 1s, the likelihood of getting it is still pretty low in comparison to the others, as it is still a 2/9 chance that you will get a 1. So, despite being a tad hopeful, chances are, I won't get a 1.

Others further communicated the difficulty of foreseeing the outcome and mentioned predicting arbitrarily as a result. One explained, "I just picked a random ball that wasn't one of the two 1's. Because you never know… ." As expected, participants used various arbitrary (nonlogical) strategies. Some chose a number they liked, as one said, "It is my lucky number." Others went with their gut feelings and frankly said so: "I just went with a gut feeling." Many of the rest simply chose a random number, as one described, "I closed my eyes, shook my cursor and it let choose."

To get a more systematic sense of these responses, we can examine how participants coded their responses according to the six reasons shown in Table 3. The six reasons represent different aspects of our proposed process, and we were interested in whether participants' verbal responses reflected any or all aspects of that process. Over half of these participants (51.7%) agreed that their response reflected, "The likelihood of drawing a 1 was small overall and/or 1 was overall unlikely to be drawn." This suggests that the absolute likelihood of the most likely outcome indeed influenced people's predictions. Even more participants resonated with the sense of low foreseeability: 80.7% agreed that their response reflected, "The drawing is random and anything could happen," and 68.3% agreed that their response reflected, "The outcome is hard to predict or know in advance."

Our account holds that this low foreseeability could promote arbitrary predictions of various kinds. Indeed, 40.7% agreed that their response reflected, "I picked a number I just liked for some reason, such as my lucky number, my birthday, my favorite number, and so on," and 66.2% agreed that their response reflected, "I guessed or picked a number at random." Finally, 71.7% agreed that their response reflected, "I went with my gut feeling." (These percentages sum to more than 100%, reflecting that these categories are not mutually exclusive.) Collectively, the six reasons covered all responses: No one answered "no" to all of them.

In Study 6a, we see that people's explanations for why their judgments and predictions diverged fit with several aspects of our proposed process. Although participants' verbal explanations may not always accurately reflect the forces that drive their behavior (Nisbett & Wilson, 1977), the fact that their verbal reports converge with our hypotheses suggests that our proposed account may capture some of the reasons that predictions diverge from most-likely assessments. Study 6b tests our proposed process in a more structured way.

Study 6b: Mediation

As noted, when making predictions about the outcome of an uncertain event, we propose that people attend to the absolute likelihood of the most likely outcome and not just its relative likelihood. We further suggest that when this absolute likelihood is small, people consider the outcome to be rather difficult to foresee and that this sense of low foreseeability promotes arbitrary predictions. Study 6a gave some empirical support for this hypothesized process. Study 6b measures perceptions of foreseeability and measures how participants claim to make their predictions to test this process more formally.

Method

Participants and Design

We preregistered to recruit 300 participants (https://aspredicted.org/83hj-47t9.pdf), and 301 completed the study. As preregistered, we excluded participants who failed the attention check (n = 15), leaving 286 participants for our analyses (M_{age} = 41.1 years; 42.7% female, 54.5% male, 1.0% nonbinary, and 1.4% preferring not to say). Participants were randomly assigned to either the low-chance or high-chance condition.

Procedure

Participants saw either the low-chance set or the high-chance set shown in Figure 1. Participants indicated which number was most likely to be drawn and then predicted which number would be drawn.

Participants next rated two sets of items. The first set contained three statements, order randomized, that asked participants what they based their predictions on: "My prediction was based on subjective or personal factors, such as a gut feeling, a lucky number, a pure guess, or something similar"; "my prediction was based on the objective probabilities of drawing different numbers"; and "my prediction was based on logic and reasoning." For each item, participants responded on a scale ranging from 0 (*disagree strongly*) to 10 (*agree strongly*).

The second set contained another three statements, order randomized, that measured how foreseeable the outcome felt: "On a scale from 0 (very uncertain) to 10 (very certain), how certain versus uncertain do you feel about which number will be drawn?"; "on a scale from 0 (very difficult to predict) to 10 (very easy to predict), how easy do you think it is to predict which number will be drawn?"; "on a scale from 0 (very unforeseeable) to 10 (very foreseeable), how foreseeable is the number that will be drawn?"

Then, participants clicked a button to draw a ball. At the end, they answered an attention check that asked them to recall how many balls were marked "1."

Results and Discussion

First, we replicated the discrepancy between predictions and likelihood judgments. Most participants correctly identified 1 as most likely regardless of whether they were in the high-chance or low-chance condition, $P_{\text{high-chance}}$ = 96.6% versus $P_{\text{low-chance}}$ = 93.4%, $\chi^2(1)$ = .97, p = .325. Predictions, however, reliably differed between conditions. Fewer participants predicted a 1 in the low-chance condition than in the high-chance condition, $P_{\text{high-chance}}$ = 91.9% versus $P_{\text{low-chance}}$ = 59.1%, $\chi^2(1)$ = 40.64, $p <$ .001. Thus, in the high-chance condition, the percentage identifying

1 as most likely did not reliably differ from the percentage predicting a 1, $P_{\text{most likely}} = 96.6\%$ versus $P_{\text{predict}} = 91.9\%$, $\chi^2(1) = 2.25$, $p = .134$. However, in the low-chance condition, there was a sizable and reliable gap between the percentage identifying 1 as most likely and the percentage predicting 1, $P_{\text{most likely}} = 93.4\%$ versus $P_{\text{predict}} = 59.1\%$, $\chi^2(1) = 42.68$, $p < .001$.

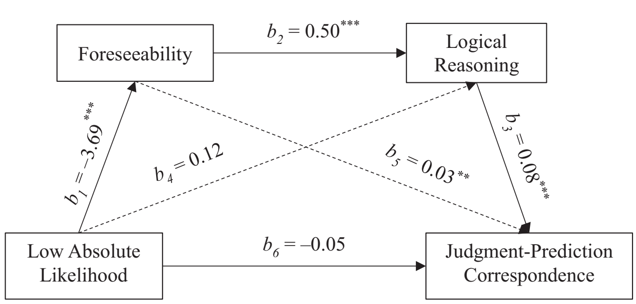
Next, we examined the means of our proposed process measures. We averaged responses to the three "foreseeability" items to create an index of how foreseeable the outcome felt ($\alpha = .93$). Scores were higher, indicating greater perceived foreseeability, in the high-chance condition ($M_{\text{high-chance}} = 6.53$, $SD = 1.70$) than in the low-chance condition ($M_{\text{low-chance}} = 2.92$, $SD = 2.12$), $M_{\text{diff}} = 3.61$, 95% CI [3.16, 4.05], $t(261.6) = 15.83$, $p < .001$, $d = 1.89$.[4]

We also averaged responses to the three "bases of prediction" items (with the first item reverse-coded) to create an index that assessed the degree to which participants reported making predictions based on logical reasoning ($\alpha = .93$). Scores were higher, indicating more reported logical reasoning, in the high-chance condition ($M_{\text{high-chance}} = 7.87$, $SD = 3.04$) than in the low-chance condition ($M_{\text{low-chance}} = 6.04$, $SD = 4.03$), $M_{\text{diff}} = 1.82$, 95% CI [0.99, 2.67], $t(252.2) = 4.31$, $p < .001$, $d = .52$.

We next tested, via serial mediation, whether the change in the absolute likelihood affected people's perceptions of the foreseeability of the outcome, which in turn corresponded to how they reported making their prediction (see Figure 4). For this analysis, we fitted the mediation model with the responses from the great majority of participants (272 of 286, or 95.1%) who correctly indicated 1 as most likely.[5] We created a dependent variable, dubbed "judgment-prediction correspondence," that would equal 1 if a participant predicted a 1 and 0 if they did not predict a 1. We included the foreseeability index and the logical reasoning index as potential mediators. Finally, we coded the independent variable, dubbed "low absolute likelihood," as 1 if the most likely number (i.e., 1) had a low chance of being drawn and 0 if it had a high chance.

Results based on 5,000 bootstrapped samples showed a statistically significant total effect of low absolute likelihood on judgment-prediction correspondence ($b_{\text{total}} = -.202$, $SE = .067$, $p = .003$). This total effect was serially mediated by foreseeability and logical reasoning, supported by a statistically significant indirect effect ($b_{\text{indirect}} = -.149$, $SE = .039$, $p < .001$). The remaining direct effect did not reliably differ from 0 ($b_6 = -.053$, $SE = .047$, $p = .258$). Specifically, the low absolute likelihood made the outcome feel difficult to foresee ($b_1 = -3.692$, bootstrapped $SE = .228$, $p < .001$).

Figure 4
Mediation



** $p < .01$. *** $p < .001$.

This lack of foreseeability corresponded to people making a prediction that was more likely to depart from logical reasoning ($b_2 = .501$, bootstrapped $SE = .117$, $p < .001$). Finally, predictions that were less logical were more likely to diverge from predictors' self-reported most likely outcome ($b_3 = .080$, $SE = .006$, $p < .001$).

Study 6b provides evidence supporting our hypothesized process for why judgments and predictions diverge when absolute likelihood is low. When the absolute chance of the most likely outcome arising is low, the outcome can feel difficult to foresee. The sense of low foreseeability corresponds to people's tendency to predict arbitrarily. Such arbitrary prediction strategies then correspond to the divergence between prediction and the most likely outcome.

Study 7: Greater Relative Likelihood

So far, we have shown that people's predictions tend to depart from their perceived most likely outcome when the most likely outcome has a low overall likelihood of arising. We suggest that this pattern arises because, instead of focusing on only relative likelihood (i.e., which outcome is more likely to arise than others?), people also consider absolute likelihood (i.e., how likely is this outcome to arise overall?).

If this is true, highlighting the relative likelihood may direct some attention back to this factor and consequently move predictions closer to likelihood judgments. One simple way to highlight relative likelihood is to make it larger. In Study 7, we thus manipulate the relative likelihood of the most likely outcome while holding its absolute likelihood constant. We predict that more people will predict in line with the obvious most likely outcome when it has a greater likelihood relative to others, even when its absolute likelihood remains low.

Method

Participants and Design

As preregistered, we recruited 600 participants from MTurk (https://aspredicted.org/hzxq-j5vy.pdf). Fourteen of them did not pass the attention check, leaving us with 586 observations ($M_{\text{age}} = 40.3$ years; 52.2% female, 47.3% male, and 0.5% selecting "other"). Participants were randomly assigned to the lower or higher relative likelihood condition.

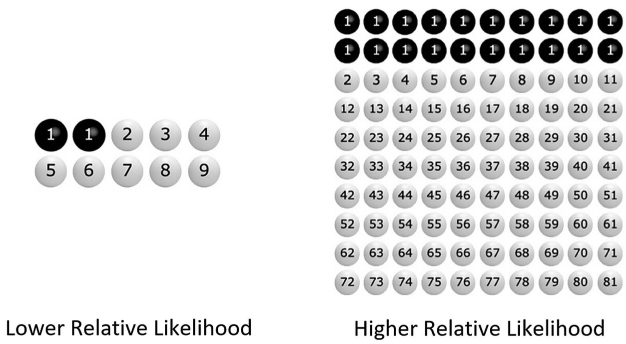
Procedure

Participants drew from one of two virtual sets of balls as shown in Figure 5. In the lower relative likelihood condition, participants drew from a set of 10 balls. Two balls were labeled "1," and the other eight were labeled a unique number from "2" to "9." In the higher relative likelihood condition, participants drew from a set of 100 balls. Twenty of them were labeled "1," and the other 80 were

[4] This and following t tests are Welch's t tests (without the assumption of equal variances). The degrees of freedom were approximated using the Welch–Satterthwaite equation (Satterthwaite, 1946).

[5] We did this because our main manipulation focused on the number 1, and so it seemed cleanest to restrict our analysis to those who reported 1 as the most likely outcome. We also fitted the model with the full sample, as reported in the Supplemental Materials. The full-sample results were consistent with the current findings.

Figure 5
Study 7 Stimuli



labeled a unique number from "2" to "81." Thus, although 1 had a 20% chance of being drawn from both sets, it was twice as likely as the other numbers in the lower relative likelihood condition but 20 times more likely than the other numbers in the higher relative likelihood condition.

Participants both predicted which number they would draw and indicated which number was most likely to be drawn in counterbalanced order. At the end of the survey, participants answered an attention check that asked them to recall how many balls were labeled "1."

Results and Discussion

Participants answered both a most-likely question and a prediction question in a counterbalanced order. We focus here on a within-subjects analysis that compares participants' responses to both questions; the Supplemental Materials contain a between-subjects analysis that uses only responses to the first question a participant saw. As in previous studies, there was a large most-likely versus prediction gap within the lower relative likelihood condition: 85.6% of the participants indicated 1 as most likely but only 57.9% of them predicted a 1, $\chi^2(1) = 54.06$, $p < .001$. However, this gap was narrowed and was not reliable in the higher relative likelihood condition, with 86.3% identifying 1 as most likely and 75.0% of participants predicting it, $\chi^2(1) = 2.07$, $p = .150$. Furthermore, among the majority of participants who correctly indicated 1 as most likely, 34.0% did not predict a 1 in the lower relative likelihood conditions whereas only 9.9% did not predict a 1 in the higher relative likelihood conditions, $\chi^2(1) = 41.13$, $p < .001$. Thus, internal inconsistency was attenuated by the greater relative likelihood. This pattern persisted in both question orders (see the Supplemental Materials).

We have suggested that the low absolute likelihood effect may arise because people focus on both relative and absolute likelihood. Study 7 suggests that we can increase the attention paid to relative likelihood, even when absolute likelihood remains low, by increasing the relative likelihood. When the most likely outcome had a greater relative advantage, predictions were less likely to diverge from likelihood judgments. That said, because we increased relative likelihood by increasing the number of balls marked "1," perhaps our manipulation also increased perceptions of the absolute likelihood of drawing a 1 (e.g., via the ratio bias; Denes-Raj & Epstein, 1994). This is possible. Supplemental Study S4 uses a manipulation that does not involve changing the likelihoods or how they are presented. Further, Study 8 manipulates perceptions of the low absolute likelihood more directly.

Study 8: Envisioning 1,000 Trials

Study 7 narrowed the most-likely versus prediction gap by increasing people's focus on relative likelihood. Study 8 examines whether reducing their focus on the low absolute likelihood of the most likely outcome also reduces this gap. In Study 8, we ask some people to first imagine the outcomes of 1,000 repeated trials before predicting for a single trial. To understand our predictions, consider drawing from a set of nine balls where the number 1 appears twice. When predicting for one trial, the chance of drawing a 1 seems low. However, when people first imagine the outcomes of 1,000 trials, drawing a 1 may no longer seem so unlikely because people could have just envisioned a 1 being drawn over 200 times. Thus, to the extent that people focus on absolute likelihood, the absolute likelihood may not seem as low following this manipulation as when people just consider one drawing in isolation. Similarly, envisioning 1,000 trials may prompt people to take an outside view and focus less on the low absolute likelihood of 1 arising on any single trial (Kahneman & Lovallo, 1993).

Thus, we predicted that people's predictions would be more in line with what is most likely when they first consider a large number of repeated trials than when they do not.

Method

Participants

As preregistered, we recruited 300 MTurk workers (https://aspredicted.org/q8p8-s3hp.pdf). Ten of them did not pass the attention check, leaving us with a final sample of 290 ($M_{age} = 43.6$ years; 47.2% female; 52.4% male; 0.3% selecting "other").

Procedure

Participants completed two tasks. In one task, participants were given the low-chance set shown in Figure 1. Before drawing a ball, participants were asked to predict which number they would draw. In the other task, participants imagined that 1,000 people were each given that set of balls, and those 1,000 people each randomly drew a ball from the set. Participants were asked to imagine that the 1,000 people were divided into eight groups based on the number that they drew, such as the group of people who drew a 1, the group who drew a 2, and so on. Participants estimated which group was the largest. The order of the two tasks was counterbalanced, so that some people predicted for a single trial before imagining 1,000 people, whereas others imagined 1,000 people before predicting for a single trial.

At the end of the study, all participants answered an attention check that asked them to recall how many balls had been marked "1."

Results and Discussion

Almost everyone (92.4%) estimated that the group of people who drew a 1 was the largest group, and this percentage did not reliably differ between task orders, $P_{\text{envision-before-predict}} = 93.8\%$ versus $P_{\text{predict-before-envision}} = 91.0\%$, $\chi^2(1) = .49$, $p = .485$.

Did envisioning 1,000 draws bring predictions more in line with the most likely outcome? It did. Reliably more participants predicted that they would draw a 1 after, versus before, they imagined 1,000 people drawing a ball, $P_{\text{envision-before-predict}}$ = 74.7% versus $P_{\text{predict-before-envision}}$ = 55.6%, $\chi^2(1) = 10.83$, $p < .001$. We further examined the predictions among the great majority who estimated that the group drawing a 1 was the largest ($n = 268$). The effect persisted. Although everyone in this subsample explicitly stated that 1 would come up most frequently among the 1,000 draws, only 61.1% predicted a 1 before considering the 1,000 draws, but 76.6% predicted a 1 after considering the 1,000 draws, $\chi^2(1) = 6.89$, $p = .009$.

One may wonder whether the effect of imagining 1,000 people arose because it mainly reminded people of the most likely outcome. Our previous studies suggest that a simple reminder is not enough to affect predictions. In Study 3, people reported the most likely number immediately before making their predictions, and yet, the most-likely versus prediction gap persisted—and was unaffected by whether predictions came before or after likelihood judgments. Such results suggest that simple reminders of the most likely outcome are not enough to improve predictions and that Study 8's manipulation improved predictions by leading people to focus less on the low single-trial likelihood of that outcome.

Study 9: Giving Advice

So far, we have shown that people may predict contrary to what they know to be the most likely outcome when the most likely outcome is unlikely to arise. In our final study, we examine the predictions people recommend to others. Will people also recommend a prediction contrary to what they know to be most likely?

Recall that, in Studies 6a and 6b, people reported being less likely to make predictions based on logic when the most likely outcome was unlikely. However, the decisions people make on behalf of others are often less biased than the decisions they make for themselves (Andersson et al., 2016; Polman, 2012). Moreover, as an advisor, people are more likely to focus on distributional information relevant to the overall utility of the population (Kray, 2000), such as, "what option would make most people better off?" Thus, we suggest that people will be less likely to depart from the accuracy-maximizing prediction and less likely to predict arbitrarily when advising others, compared to when predicting for themselves.

In addition, previous research has found that the act of giving advice to others can even make people less biased in their own decisions (e.g., Fantino & Esfandiari, 2002). Thus, we also examine whether giving advice can serve as a debiasing method that brings people's own predictions closer to their likelihood judgments: If people give logical advice to others, will their own predictions follow suit?

Method

Participants and Design

Undergraduate students ($N = 281$; $M_{\text{age}} = 19.5$ years; 54.4% female) from a U.S. university participated for course credit. They were randomly assigned to one of two conditions: predict-first and advise-first. This study was preregistered (https://aspredicted.org/2drn-f8nh.pdf).

Procedure

Participants played a computerized game in the lab. Each participant saw on the screen the low-chance set from Figure 1. Participants in the predict-first condition first predicted which number they would draw. They could win a small prize (a keychain, a lanyard, or a key tag) if their prediction was accurate. After they made their own prediction, they were instructed to give advice to the participant next to them. To do this, they wrote on a piece of paper the number that they would advise their neighbor to predict. Participants in the advise-first condition first wrote advice to their neighbor. Then, they made a prediction for themselves with the same incentive as in the other condition. At this point, all participants had both made a prediction for themselves and had written advice to their neighbor. The experimenter then facilitated the exchanging of written advice.

After everyone received written advice from another participant, they were given a chance to revise their prediction. Then, they were asked to indicate which number was most likely to be drawn. Finally, they clicked to draw a ball.

Results and Discussion

As before, nearly everyone (93.2%) indicated that they were most likely to draw a 1, and this percentage was not affected by question order, $P_{\text{predict-first condition}}$ = 91.2% versus $P_{\text{advise-first condition}}$ = 95.1%, $\chi^2(1) = 1.13$, $p = .288$. However, their advice differed strikingly from their predictions. To make a clean comparison between advice and predictions, we compared predictions in the predict-first condition to advice in the advise-first condition, as preregistered. Reliably more participants advised others to predict a 1 than predicted a 1 for themselves, P_{advise} = 89.6% versus P_{predict} = 58.4%, $\chi^2(1) = 34.22$, $p < .001$. In addition, the most-likely versus prediction gap was larger than the most-likely versus advice gap: Among the great majority who correctly indicated 1 as most likely, 37.6% in the predict-first condition did not predict a 1, whereas only 7.6% in the advise-first condition did not recommend a 1, $\chi^2(1) = 33.50$, $p < .001$. Thus, although people tended to predict contrary to their likelihood judgment, their advice to others was much more in line with what they knew was most likely.

Did giving advice improve advisors' own predictions? It did. Significantly more people predicted a 1 after versus before advising others, $P_{\text{advise-first condition}}$ = 77.8% versus $P_{\text{predict-first condition}}$ = 58.4%, $\chi^2(1) = 11.31$, $p < .001$. Among those who indicated 1 as most likely, 37.6% did not predict a 1 in the predict-first condition, whereas only 19.7% did not predict a 1 in the advise-first condition, $\chi^2(1) = 9.46$, $p = .002$. Thus, giving advice brought people's predictions closer to what they knew to be most likely.

Finally, we examined people's revised predictions. Overall, only 11.7% of participants revised their predictions after receiving the advice, and this percentage did not differ between conditions, $P_{\text{advise-first condition}}$ = 11.8% versus $P_{\text{predict-first condition}}$ = 11.7%, $\chi^2(1) < .001$, $p > .999$. The Supplemental Materials contain additional preregistered analyses that support this study's main conclusions.

Study 9 demonstrates two things. First, it shows a boundary of the disconnect between prediction and judgment: Although people may not predict what they believe to be most likely, their recommended predictions to others are much more in line with their perceived most likely outcome. Second, it shows that giving advice can be a debiasing method that encourages advice-givers to subsequently predict more in line with their perceived most likely outcome.

General Discussion

If one wants to maximize the chances of accurately predicting the outcome of an uncertain event, one should predict whichever outcome one believes is most likely to arise. However, we show that people's predictions can disagree with their own likelihood judgments. Although people regularly predict their perceived most likely outcome when they think the most likely outcome is overall very likely to arise, they less regularly predict that outcome when it is overall unlikely to arise—even though they still believe that outcome to be most likely. Studies 1 through 5 documented this basic pattern in a variety of real and hypothetical contexts.

This disconnect between prediction and likelihood judgment suggests that people consider not only relative likelihood (i.e., which outcome is more likely to arise than others?) but also absolute likelihood (i.e., how likely is this outcome to arise overall?). We argue that when people think that the absolute likelihood of the most likely outcome is very low, they consider the eventual outcome to be rather difficult to foresee, and that this feeling of low foreseeability promotes arbitrary prediction strategies that lead predictions to depart from the perceived most likely outcome. Studies 6a and 6b supported this hypothesis.

It follows that one can encourage people to predict more in line with their perceived most likely outcome by redirecting their focus back to relative likelihood or reducing their focus on the low absolute likelihood. Studies 7 and 8 suggest that this is the case. Nonetheless, although people's predictions tend to diverge from what they believe to be most likely to arise, Study 9 shows that their advice to others is more in line with their believed most likely outcome.

Relation to Previous Research

Previous research on prediction and subjective probability mostly focuses on how people's predictions and judgments depart from formal probability models. As discussed, a long line of research has shown that predictions and probability judgments can be biased by many different factors. This body of research usually does not examine the correspondence between people's predictions and their likelihood judgments, instead often reasonably assuming that predictions follow from such judgments. In contrast, the current research examines the correspondence between people's predictions and their likelihood judgments, putting aside whether those predictions or judgments are biased compared to formal models.

As discussed, previous research has documented a few cases of discrepancies between likelihood judgments and predictions, including cases related to desirability bias (e.g., Park et al., 2023) and probability matching (i.e., Koehler & James, 2009). Researchers have also shown a mismatch between likelihood judgments and choice caused by the ratio bias (e.g., Denes-Raj & Epstein, 1994). The current research adds to the literature by identifying another, potentially even more pervasive, factor that causes a discrepancy between predictions and likelihood judgments: a low absolute likelihood of the most likely outcome. Because the absolute likelihood of the most likely outcome is a basic and inherent property of an uncertain event, prediction distortions caused by it may arise frequently.

Our framework makes predictions that differ from previous research. First, whereas research on the desirability bias found that prediction and likelihood judgment diverged when one outcome was particularly desirable (e.g., if participants would win money if that outcome obtained), the low absolute likelihood effect does not hinge upon one outcome being more desirable than the others. Rather, our effect might arise whenever people focus on the low absolute likelihood of the most likely outcome, regardless of the desirability of any outcome.

Second, whereas probability matching is most relevant when people predict a class of events, the low absolute likelihood effect can arise when people predict a single event. Would probability matching predict a similar discrepancy for a single prediction? Not necessarily. Imagine that an individual predicts the outcomes of N repeated draws with a 70% chance of red on each draw and a 30% chance of black. Probability matching would hold that people would predict red for 70% of the draws and black for 30%, despite knowing that red was more likely on each draw. If $N = 1{,}000$, they would predict red for 700 draws and black for 300. If $N = 10$, they would predict red for seven draws and black for three. If $N = 1$ (i.e., when they only predict a single draw), they again should be more likely to predict red than black, in line with their likelihood judgment. Thus, probability matching would not easily account for the effects seen here, which emerge on a single trial. That said, we acknowledge that there is similarity between the two effects, especially when people make multiple predictions, and we would welcome research that further investigated commonalities between them.

Last, the low absolute likelihood effect differs from what the ratio bias would predict. In our paradigm, people choose among a set of possible outcomes as their prediction. The most likely outcome from the set has both the highest likelihood and the greatest frequency (i.e., the greatest numerator of a ratio). Therefore, even people showing a ratio bias would still predict the most likely outcome, as predicting it would give them the most chances to win.

Future Directions

On the Absolute Likelihood

What makes an outcome seem likely or unlikely? For most studies in this article, we manipulated the overall likelihood of the most likely outcome by setting the low likelihood near 20% and the high likelihood near 70%. Prior research suggests that people generally perceive such likelihoods as "unlikely" and "likely," respectively (Budescu & Wallsten, 1995; Clark, 1990; Sirota & Juanchich, 2015; Theil, 2002). We also examined more natural settings where people reported their own beliefs about the absolute likelihood of basketball teams winning; that likelihood varied across a wider range (Study 5 and Supplemental Study S3). To broaden our conclusions, in a separate study (Supplemental Study S5), we sampled a wide range of likelihoods from 10% to 90% to examine our effect at different levels of likelihood. As our framework predicts, the most-likely versus prediction gap tended to shrink when the absolute likelihood increased. The gap shrank noticeably once absolute likelihood exceeded 30%. These are first steps to understand the low absolute likelihood effect over a wider and more continuous scale of absolute likelihoods. Of note, a given level of likelihood could seem low or high in different contexts, and so future research could explore the low absolute likelihood effect by using framing or other contextual manipulations to affect whether a given level of likelihood (e.g., 35%) seems high or low.

On Variants of Uncertainty

Previous research has distinguished two types of uncertainty, an internal uncertainty that is epistemic and attributed to a lack of knowledge or information and an external uncertainty that is aleatory and attributed to the properties of the environment (Fox & Ülkümen, 2011; Kahneman & Tversky, 1982). In most studies, we displayed all possible outcomes and their likelihoods to participants, so the uncertainty was external and aleatory. In Study 5 and Supplemental Study S3, when participants predicted the outcome of a basketball tournament, many might not have complete information or expertise about the tournament. Therefore, the uncertainty in those studies may have been relatively internal and epistemic. In all studies, however, we consistently observed the low absolute likelihood effect. Thus, the disconnect between prediction and likelihood judgment seems to arise regardless of whether the uncertainty is more aleatory or epistemic. That being said, we have not systematically gauged how differences between these types of uncertainty could affect the disconnect between prediction and likelihood judgment. Future research could provide a more thorough understanding on this front.

On Larger Incentives

In Studies 1, 5, and 9, as well as in Supplemental Studies S2, S3, and S4, participants were given a monetary or tangible incentive for accurate predictions, and yet the low absolute likelihood effect persisted. However, these incentives were not large in value, and one might argue that people might not have been adequately motivated to make accuracy-maximizing predictions (i.e., the downside of an incorrect prediction was not large). What would happen if the stakes were higher? One might argue that predictions would be more accurate, but one could argue the opposite. When low-chance outcomes are associated with very high stakes, an accurate prediction could feel even more like a matter of luck, and correspondingly, people could be even more drawn to an arbitrary strategy that relies on a lucky number or gut feeling. Future research could explore the potential effects of larger incentives.

On Different Goals

Could people sometimes predict an outcome that is not the most likely outcome because doing so is fun and exciting or makes the predictor feel unique? Relatedly, could prediction activate a different set of goals (e.g., “try to outsmart others”; “pick a longshot”) compared to likelihood judgment? This is certainly possible, but note that predictions and likelihood judgments only diverge when absolute likelihood is low, not high. If our effects were driven purely by fun-seeking, by a uniqueness motive, or by the activation of a particular goal, one might expect the effects to also appear in the high absolute likelihood conditions, where diverging from the most likely outcome might even be more exciting and might convey uniqueness or foresight especially well. That said, choosing an option to feel unique or to fulfill a goal beyond accuracy could, broadly speaking, be a type of nonlogical, arbitrary prediction strategy, much like choosing an option one likes or going with a gut feeling. Thus, finding that predictions are influenced by uniqueness or some other goal in low absolute likelihood settings would not be inconsistent with our account.

Implications

Prediction is everywhere. Voters predict the winner of an election; sports fans predict game outcomes; policy makers predict which alternative policy is most efficient, and so on. There is also a large, growing prediction market of sportsbooks, casinos, and online prediction and gambling platforms. Correspondingly, much research has investigated human predictions and likelihood judgments. Researchers often assume, either explicitly or implicitly, that people’s predictions follow from their subjective likelihood judgments: If their likelihood judgments are biased, their predictions will follow suit, but if their likelihood judgments are unbiased, so too will be their predictions. However, we show that predictions can easily depart from likelihood judgments. This discrepancy calls for research attention to the (non)correspondence between an individual’s prediction and their own subjective probability and suggests that even when people assess outcome probabilities correctly, their predictions might still not be optimal.

Constraints on Generality

The current research examines predictions and likelihood judgments of participants only in the United States, which is a Western, educated, industrialized, rich, and democratic society (Henrich et al., 2010). We lack evidence with participants from non-Western, educated, industrialized, rich, and democratic societies. Also, our study designs and measurements require participants to understand some basic concepts such as prediction, likelihood, probabilistic events, and random selection. We cannot assume that the exact study designs and measurements in this research would obtain similar results with people who are unfamiliar with those concepts. That said, we believe that the low absolute likelihood effect applies beyond the barrier of understanding the idiosyncrasies of specific study designs or measurements. Moreover, because we obtained convergent results in both clean experimental settings and noisier real-life cases, we expect our findings to generalize to many other scenarios.

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