Organizational Behavior and Human Decision Processes 193 (2026) 104476

Contents lists available at ScienceDirect

Organizational Behavior and Human Decision Processes

journal homepage: www.elsevier.com/locate/obhdp

People prefer novices for advice generated from direct experience and experts for advice generated from data synthesis and extrapolation

Katie S. Mehr [a,*], Matt Meister [b]

[a] Alberta School of Business, University of Alberta, Edmonton, AB, Canada
[b] School of Management, University of San Francisco, San Francisco, CA, USA

ARTICLE INFO

Keywords:
Experts
Novices
Opinions
Advice
Expertise
Message sources
Source similarity
Decision making

ABSTRACT

People are often exposed to advice and opinions from both "novices"—people with relatively limited domain experience—and "experts"—people with relatively deeper domain experience. This manuscript explores whether people (i) rely on both groups equally, (ii) consistently favor one over the other, or (iii) rely on novices in certain contexts and experts in others. Across six preregistered studies, we find evidence for the third possibility, and show that the fit between the advice generation process and expertise affect reliance on advice. Specifically, people rely more on novices for advice and opinions from direct lived experience and experts for advice or opinions from data synthesis and extrapolation. This is because people think novices have experiences that are more similar to the ones they will have, while experts do not, but may be better at synthesizing and extrapolating from data. Notably, this distinction is not simply about the domain being advised, but is specific to the advice generating process—in a given domain, people's reliance on novices and experts can be manipulated by changing their understanding of how the advice or opinion was generated. This pattern of results is generalizable to many domains (e.g., job choice, product ratings). Further, our results build on previous work highlighting from whom people seek advice and opinions, and provide practitioners with insight into when people may be more or less likely to rely on their advice and opinions.

The opinions of others are a commonly used aide in decision making, especially when a decision maker is relatively naïve (Ache et al., 2020; Barneron & Yaniv, 2020; Collins et al., 2011; Danziger et al., 2012; Hütter & Fiedler, 2019; Sah et al., 2013; Yaniv, 2004; Yaniv & Choshen-Hillel, 2012). Whether deciding how to invest their money, what product to buy, or whether to bet on a given sports team, novices often seek advice to supplement their own, limited knowledge (Zhang et al., 2022). Therefore, the opinions of others supplements decision makers' existing knowledge with additional information gleaned from expertise and experience that an individual decision maker lacks.[1]

Decision makers can opt to solicit advice and opinions from a wide array of sources. In this manuscript, we focus on two broad categories of advice-givers. One such category is "novices"—people with relatively limited domain experience.[2] The other category is "experts"— people with relatively deeper domain experience. Crucially, novices are likely to be perceived to have similar experiences to decision-makers because advice-seeking decision-makers are also likely to have limited experience, and thus are perceived to experience things (e.g., investments, products, etc.) similarly. Experts are likely to be perceived to have dissimilar experiences to decision makers because experts' domain knowledge may be seen to change how they experience and evaluate a situation.

Seeking advice and opinions from both groups has merit. There are often large samples of novices, while experts may be perceived by naïve

* Corresponding author.
E-mail addresses: kmehr@ualberta.ca (K.S. Mehr), mmeister@usfca.edu (M. Meister).

[1] Although prior research identifies a distinction between advice and opinions—with advice being more relied upon due to its seeming intention to help the advisee with a specific problem (Milyavsky & Gvili, 2024)—we focus on both advice and opinions, and often use both words throughout the manuscript as a result. We do so because our focus is on the interaction of source (novice v. expert) and advice/opinion generation (from experience v. from data synthesis), which we anticipate to be orthogonal to the distinction between opinion, which is a judgment or view, and advice, which is delivered with intention to help the advisee with a specific problem. Empirically, we test opinions in Studies 1–3 and 6, while we test advice in Studies 4–5; our results are robust to both advice and opinions.

[2] Note that, while not everyone is a novice in every domain, most people are not experts in a given domain. Therefore, while individual decision makers may think themselves closer to "experts" than what we deem "novices" in an individual domain, across the population, most people are novices.

https://doi.org/10.1016/j.obhdp.2026.104476
Received 29 July 2025; Received in revised form 1 February 2026; Accepted 5 February 2026

decision makers as more objective and as having a unique ability to form advice and opinions through data synthesis and extrapolation, along with controlled tests. For example, someone looking to invest in the stock market might consider advice from friends, family, or internet forums because they believe those novices have similar financial standing, time constraints, and abilities to the decision maker, along with the common goal of savings. As well, one may seek advice from investment professionals because they believe those experts are more sophisticated in that they know how to synthesize and extrapolate from financial data and are not limited in the same ways. Similarly, expecting parents can inform their decision of whether to buy a given stroller by considering consumer reviews (provided by novices)—other real parents who have used the stroller in daily life—in combination with experts such as Consumer Reports, New York Times' Wirecutter, and more—those who, rather than using a single stroller in daily life, compare the universe of strollers using controlled tests and analysis of specifications in order to make recommendations.

In this manuscript, we aim to determine when and why people rely on advice from experts and novices. Our goal is to contribute to the broad literature on advice-taking and inclusion of opinions (Barneron & Yaniv, 2020; Blunden et al., 2019; Collins et al., 2011; Harvey & Fischer, 1997; Hofmann et al., 2009; Milyavsky & Gvili, 2024; Yaniv, 2004; Yaniv & Kleinberger, 2000). Specifically, we find that people rely more strongly on the advice and opinions of novices when they believe that advice or opinions are formed from *direct lived experience* (e.g., typically present in the form of product or company evaluations). However, people rely more strongly on the advice and opinions of experts when they believe that the advice or opinion is formed from *synthesis and extrapolation of data* (e.g., typically present in the form of predictions of future events). This pattern emerges because people think novices are more likely to have experiences in that particular setting that are similar to their own, as they think novices learn about and experience given domains for the same goals as the decision maker. However, people believe experts are able to synthesize and integrate potentially complex data. Importantly, this distinction is specific to the advice or opinion generating process—in a given domain, people's reliance on novices and experts can be manipulated by changing their understanding of how the advice or opinion was generated. We find evidence of this across six studies, testing a range of contexts, including advice about which job offer to accept and opinions of how much someone will enjoy different consumption experiences.

These findings provide unique theoretical and practical implications. Previous work has highlighted similarity in general as an important factor influencing reliance on opinions and advice; specifically, that people often rely on advice and opinions of similar others (Essig, 2024; Yaniv et al., 2011). However, other work suggests people value advice and opinions from experts in many cases (Harvey & Fischer, 1997; Meshi et al., 2012). Only limited work has looked across situations to understand what factors lead people to rely more on novices and experts. An important exception comes from a conference proceeding by Fadel et al. (2022), who focus on the effects that differences in situational characteristics (as perceived by advice-seekers) have on reliance on novices and experts. Fadel et al. (2022) specifically consider online discussion forums where both novices and experts provide advice (e.g., StackOverflow), and find that advice-seekers' *perceptions* of (i) what skills are important for advice providers to have for a given situation (e.g., specialization of knowledge vs. lived experience), (ii) how the problem itself is defined (e.g., subjectivity/objectivity, commonness of experience), and (iii) what the solution that problem requires (e.g., complexity) affect reliance on novices and experts. Crucially, our work compliments this proceeding in at least two ways: (i) by considering ways to seek advice beyond online forums, and (ii) by identifying the role of factors that advice providers can manipulate (specifically, how advice was generated), rather than stable situational characteristics as perceived by advice seekers. Thus, our contribution is directly actionable for managers and advice providers.

Our manuscript supports the notion that both novice and expert advice and opinions are valued in general, but that the relative value of each is context-dependent—people's use of advice and opinions from each group critically depends on how the advice was formulated. Practically, our results help firms understand when people will rely on different sources to make judgments. For instance, an expert who wants their advice or opinion to appear more compelling might highlight the extensive data they reviewed to generate it.

1. Conceptual Development

According to a large literature on social influence, people are influenced by the attitudes and opinions of those around them (Cialdini & Trost, 1998; Deutsch & Gerard, 1955; Kelman, 1958; McDonald & Crandall, 2015; Pornpitakpan, 2004; Wood, 2000). In particular, the advice-taking literature suggests that people seek out and rely on advice and opinions to make decisions (Blunden et al., 2019; Hofmann et al., 2009; Phillips, 1999; Sah et al., 2013; Schrah et al., 2006), though not blindly, as they often underweight the advice and opinions they receive (Bonaccio & Dalal, 2006; Harvey & Fischer, 1997; Yaniv, 2004). Social influence research distinguishes between both normative (i.e., the desire to maintain social norms and relationships) and informational social influence (i.e., decision makers' desire to optimize; Deutsch & Gerard, 1955), with our manuscript focusing on the latter form—decision makers' desire to make better decisions.

In pursuit of making better decisions, several factors influence how heavily people rely on the advice they receive. For instance, characteristics of the advice play an important role. Advice or opinions that include language signaling concern for the recipient's social identities is more relied upon (Goldsmith, 1999), because such concern seems additionally respectful and unthreatening to the receiver. Advice or opinions that have been purchased is more relied upon than free advice (Patt et al., 2006) due to the perceived credibility that comes with payment. Indeed, even the label of advice as either opinions or advice changes people's reliance on it; in particular, people rely more on advice because it is seen as more trustworthy (Milyavsky & Gvili, 2024). Finally, Van Swol & Ludutsky (2007), found that advisors who extensively shared the information that led to their advice or opinions were more strongly relied upon, as this explanatory information helps receivers to evaluate the fit of the advice or opinion, and makes advisors appear more credible.

Likewise, characteristics of the advice recipient affect reliance on advice and opinions. People who perceive themselves to be relatively higher power than advisors are less reliant on advice and opinions (See et al., 2011), as are people who think the advice or opinion will benefit the advisor (Sah et al., 2013). Recipients who are themselves more expert also rely on advice and opinions less, as they can recruit more information of their own when evaluating both a target and advisor (Yaniv, 2004).

Of particular interest to the current research, however, is a third factor—characteristics of the advisor(s) themselves. Generally, people rely on advice or opinions from sources that they see as credible in a given domain. For instance, Pornpitakpan (2004) reviews relevant literature in social influence and highlights many cases in which people rely more on advice and opinions from those they see as credible, including when receiving job performance feedback, considering whether to accept or reject suggestions from others, and viewing advertisements for products. We specifically focus on credibility that arises from two distinct sources—perceived expertise and direct similarity of experience.

A broad and long-standing literature demonstrates that credibility of advisors is often associated with perceived expertise (Giffin, 1967; Hovland et al., 1953). Most closely to our research, Jungerman and Fischer (2004) theorize that in dyadic decision situations (where there is a single advisor and a single advisee), people are less reliant on novice advisors than on advisors with domain expertise.[3] This is consistent with related empirical research, which has argued that people are more likely to follow advice in knowledge-based domains when it comes from advisors who recipients perceive as having domain expertise. For instance, people indicated in recall experiments that they were more likely to follow past advice when it came from someone with relevant domain knowledge (Feng & MacGeorge, 2006). Similarly, when given estimates from multiple advisors, people were more likely to rely on advice and opinions from a confident advisor because they perceived confidence as meaning the advisor was more proficient in the relevant topic (Price & Stone, 2004). Further support for the notion that domain expertise predicts the extent to which an advisor is relied upon can be found from less direct sources. For instance, people have been shown to follow those they deem as having authority, which is often also associated with expertise (Hoffman et al., 1995). For example, some work finds that people are more likely to comply with a request if the requester was seen as legitimate, most often demonstrated via clothing showing authority, like a uniform (Bickman, 1974; Bushman, 1988). Taken together, this work shows that perceptions of domain knowledge can affect advice taking by making advisors appear more credible—at least in some domains.

Meanwhile, the literature also documents several cases in which people do not rely on those who they perceive to be experts, instead relying upon advice and opinions from novices—people who do not necessarily have expertise, but are assumed to experience things for similar reasons to those of the decision maker. A simple example of this distinction comes from people living with chronic diseases (Fox, 2013). While these patients claim to rely upon medical professionals (i.e., experts) for diagnoses, they claim to turn to non-professional people like them for practical, day-to-day advice. Fox interprets this as evidence that, for certain aspects of the experience, people value learning from the lived experience of similar others. This is consistent with research in the context of product beliefs, where Essig (2024) found that people rely more on novice (vs. expert) ratings for products. Essig finds that this reliance is because people believe that novices base their opinions on how it feels to use the product, and that a novice's experience using the product will be similar to the decision maker's. Finally, in organizations, people also seem to rely on advice from novices—in a recent network study of downsizing events, employees sought advice from novices rather than higher-level colleagues for this reason (Aalbers & Smit, 2025).

While our research focuses on informational social influence (influence that drives from decision makers' desire to optimize their lives), research on normative social influence (influence driven by decision makers' desire to keep social cohesion) also shows that people rely on similar others. For instance, when people are told what the vast majority of people who are like them do (e.g., provided a descriptive norm), they behave in accordance with that norm, by doing things like reusing a hotel towel if they read that the majority of other hotel guests have done so (Goldstein et al., 2008) and recycling if the majority of others have (Schultz, 1999). This is because social norms describe what is desirable in that setting (Miller & Prentice, 1996), and people often seek acceptance from novices via behaving like they do (Cialdini et al., 1991). One key aspect affecting the likelihood that people follow advice and opinions from novices is how similar those novices are to themselves. For instance, people are more likely to cooperate with (Parks et al., 2001), follow the norms of (Rimal et al., 2005), and follow recommendations of similar others (Hilmert et al., 2006).

Thus, the current literature clearly demonstrates that people value both experts and novices, though not equally in all contexts. Instead, some contexts find reliance on novices, while others find reliance on experts. A remaining question is what specific factors affect people's reliance on novices and experts. One suggested framework by Fadel et al. (2022) focuses on the perceived characteristics of situations where advice is being sought—which advice providers may have little control over.

Fadel et al. (2022) considered the context of online discussion forums where both novices and experts can make contributions. In one survey of 110 participants with 20 hypothetical decision situations (where participants indicated the extent to which they would seek online advice or opinions from novices and experts before listing characteristics of each situation) and a follow up conjoint study of 231 participants with two situations, those authors found that how people perceive the characteristics of a situation (e.g., what expertise advisors need, the objectivity and/or commonness of a problem, and the complexity of necessary solutions) affect reliance on novices and experts. For example, Fadel et al. (2022) found that problems that are seen as more objective and less commonly experienced led to reliance on experts, with the opposite leading to reliance on novices. However, their research is limited to perceived situational characteristics, and thus did not identify factors that advice providers have control over. Further, their research did not consider advice seeking outside of online forums, which we do. Thus, the current research compliments theirs, by explaining when and why people might rely on novices and experts across domains and outside of specific online forums, specifically identifying the role of advice generation—a factor that advice providers can control.

In particular, we highlight when people find a "fit" between the advice generation process and the group providing advice (Evers et al., 2014). When people see these two things as fitting together, they rely more on the advice or opinion. We find that a given domain itself is not what leads people to perceive fit; instead, fit results from the process through which advice is generated. In cases where advice or opinions are generated through lived experience (directly having the same experience that a decision maker anticipates themselves), we find that people rely on advice or opinions from novices, as they believe novices' lived experiences in the focal domain to be most similar to their own. Alternatively, in cases where advice is generated through synthesizing and extrapolating from potentially sophisticated data, we find that people rely on experts, whom they anticipate to have these skills. Below, we expound upon this distinction.

First, people might seek advice from novices when direct lived experience with the focal decision is important. For instance, when evaluating product ratings, people want to know what it is like to use the product for one's own, personal use, which novices with direct experience can speak to (Essig, 2024). Even in downsizing situations, people want to hear from similar others who have had direct, relevant experience (e.g., by having been laid off during downsizing themselves; Aalbers & Smit, 2025).

These results are consistent with the broader notion that experts often have categorically different direct experiences from novices (the majority of the population), likely because their domain expertise changes how they experience a given context. For example, while both experts and novices may "experience" a baby stroller, their experiences are very different. Novices focus on the same characteristics as most decision makers—they invest to grow their money while managing risk, purchase a baby stroller to haul children around daily life for months at a time, and choose between potential airline flights to minimize discomfort and maximize ease. Novices also likely only experience a very limited set of alternatives—if more than one. Meanwhile, experts' domain knowledge changes the aspects of the experience they notice and focus on (Daley, 1999; Rota & Zellner, 2007). And, experts could experience many more alternatives, in part due to their domain

[3] Though closely related to our work, Jungerman and Fischer's theoretical paper focuses on effect of information asymmetry in dyads, which is a much different context than ours.

knowledge. This difference in knowledge of alternatives leads to fundamentally different comparisons (Hsee, 1996). For example, food experts may have higher standards than regular people, or put weight on aspects like proper service etiquette, while regular people may just want to have a good meal within their budget. If people are aware of this difference in how novices and experts have—and then evaluate—experiences, they will prefer novice opinions (vs. expert) when those opinions result from experience. Formally:

H1: People will be more likely to rely on novices for advice or opinions generated from direct, lived experience.

Examples from the prior literature clearly lead to H1, in that there are many cases in which people follow novice advice that is based on lived experience. In contrast, there is less of a clear distinction from prior research as to when people will follow expert advice—merely that they do. In reality, it is possible that valuing experts' advice and opinions is the baseline, with novice advice and opinions being valued only in cases where they result from direct lived experience. More concretely, however, in many of the cases in which expert advice and opinions are valued—and indeed, in which certain experts are more valued than others—advice and opinions are formed from sophisticated synthesizing and extrapolating from abstract data. This is one thing that relatively deeper domain expertise allows for—to take potentially complex and disparate data and form an opinion or advice. For example, complex models using different inputs can improve stock forecasts (Rapach & Zhou, 2013), weather forecasts (Krishnamurti et al., 2016), and employee turnover (Zhu et al., 2017). Most people are often not well-versed in these complicated models, and the more simplistic heuristics they may use to make judgments from data are often inaccurate (Kupor et al., 2019; Stephens et al., 2015). Research shows that people are aware of their own shortfalls in this way (Yaniv & Kleinberger, 2000), which suggests that they value experts—who have relatively deeper domain expertise—for advice or opinions that result from this data synthesis and extrapolation:

H2: People will be more likely to rely on experts for advice or opinions from synthesis and/or extrapolation of abstract data.

We note that while we have discussed examples where the decision domain focuses on direct experience v. data synthesis and extrapolation, our predictions are broader, and studies do not only vary domain. Specifically, our predictions are about the advice or opinion generating process—whether it is from experience or data—and our studies test this as well. This is an important distinction, as it relaxes the constraints on advisors. If people are truly influenced differently by how novices and experts formed their advice, it is possible to manipulate what advice will be valued within a given domain. This should allow advice or opinion providers to tailor messaging in more effective ways.

2. Overview of studies

We test our hypotheses across six experiments (see Table 1). Study 1 tests whether there is a correlation between people's preference for experts or novices and their perceived importance of direct experience or data synthesis for a number of domains. It also measures what characteristics people associate with novices or experts. Study 2 manipulates opinion generation by changing domain; specifically, we test whether, when shown numerical advice from novices and experts, people rely more on novices or experts for a number of different domains. Studies 3, 4, and 5 hold domain constant and manipulate whether novices and experts came to their opinions (Study 3) or advice (Studies 4 and 5) via data, direct experience, or something in between. In Study 3, both groups provide predictions of how likely it is that someone would enjoy different experiences (e.g., a sporting event or ski hill), and both groups are described as arriving at these opinions based on direct experience or data. In Study 4, participants imagine having two job offers and receive advice from a novice and expert; both parties form advice based on direct experience, data, similar experience, or observed experience about both companies. Study 5 tests for the possibility that the advice-generation manipulation acts as a proxy for situational characteristics (e.g., as suggested by Fadel et al. (2022)) by manipulating these characteristics directly, and testing whether the previously established effects are moderated. In Study 6, we manipulate how similar a novice's experience is to the decision makers, demonstrating that when a novice's experience is less similar, decision makers rely less on the novice's opinion. Lastly, Study S1 in Supplementary Materials F replicates two conditions from Study 4 while labeling the novice as a friend, rather than colleague. All materials, data, code, and pre-registrations can be found in Research Box: https://researchbox.org/2597.

3. Study 1

Study 1 had three goals. First, it tested the correlation between people's choice of novices or experts and their judgment of how important opinions based on direct, lived experience or synthesizing and extrapolating from data is for various domains. Given H_1 and H_2, we predicted that this correlation should be significant, as people should be more likely to choose novices for opinions in which direct, lived experience is important, and experts for opinions in which synthesizing and extrapolating from data is important. Second, it tested whether people were more likely to choose novices for domains we hypothesized as involving opinions from direct experience, and experts for domains we hypothesized as involving opinions from data.[4] Lastly, to understand what people think of the labels "experts/critics" and "peers/everyday people", Study 1 also asked participants to rate both groups on a number of adjectives.[5]

3.1. Method

Participants. We recruited online participants from Connect by CloudResearch. Using a pre-registered interim analysis design (PRIAD; André and Reinholtz (2024)), we preregistered a sample size of 700 participants with two interim analyses at 140 and 280 participants. Because our *p*-value of interest was below the cutoff specified by our PRIAD ($p < 0.02199$), we only collected 140 participants. As preregistered, we removed data from two participants who did not submit their ID for approval on the Connect platform. Our final sample comprised 140 participants ($M_{Age} = 39.84$, 52.86% male, 47.14% female).

Procedure and design. Participants were randomly assigned to either the *choice* or *response* condition. Across both conditions, all participants considered ten different domains, each on a separate page and in a random order. These ten domains were: house listing price, investment decision, job quitting rate prediction, number of units sold by a company prediction, sales by a given sales team prediction, craft beer selection, work shirt selection, event space for a work event selection, restaurant for lunch selection, and furniture for an office selection.

In the *choice* condition, participants considered whether, for each domain, they would rather get information from experts/critics (coded as 1) or peers/everyday people (coded as 0). For example, the text participants read for the event space domain was (emphasis in original): "Imagine you're looking to find **an event space for an office holiday party** and are trying to determine **which event space to book.** You can get information about **event spaces** from one of two groups: everyday people/peers or critics/experts. Who would you rather get information about **event spaces** from?" After selecting one of the two groups for

[4] While this study tests people's choice of advice source (e.g., novice or expert), all other studies test reliance on advice from each group.

[5] In Studies 1–3, we do not use the label "novice" and instead use either "everyday people" or "peer." Studies 4–5 incorporate a colleague as a novice, while Study 6 describes someone who flies from time to time.

Table 1
Overview of Studies.

Study	Question(s) tested	Manipulation	Domains tested	Type of advice given	Dependent measure
1	Do people choose to receive opinions from novices or experts for various domains? Is there a correlation between choice and perceived importance of an opinion based on direct experience or data? What qualities do people associate with novices and experts?	Domain	*Opinions from direct experience:* Choosing a craft beer, work shirt, event space for a work event, restaurant for lunch, office furniture *Opinions from data:* Determining a listing price of a house, investments, how many people will quit at a given company in a year, how many units of product a company will sell, how many sales a sales team will make	No advice given	Choice of group to receive opinions from
2	Do people rely on novices or experts more for various domains when viewing opinions from both groups?	Domain	*Opinions from direct experience:* Buying the following products: a child's car seat, craft beer, a TV *Opinions from data:* Predictions in the following domains: stocks, rainfall, sports, housing prices, election outcomes	Numeric	Likelihood evaluation
3	Do people rely more on novices for opinions from direct experience and experts for opinions from data when domain is held constant?	Whether direct experience or data was used to formulate opinions	Predictions of enjoyability in the following domains: sports, movies, skiing	Numeric	Enjoyability evaluation
4	Does people's reliance on advice depend on whether it was formed from direct experience, similar experience, observed experience, or data when domain is held constant? Are advice-generation manipulations simply acting as proxies for situational characteristics identified by Fadel et al. (2022)?	Whether direct experience, data, similar experience, or observed experience was used to formulate advice	Selecting a job offer to accept	Verbal	Likelihood of accepting each offer
5	Does manipulating situational characteristics identified by Fadel et al. (2022) affect the strength of the advice-generation manipulation?	Whether direct experience or data was used to formulate advice	Selecting a job offer to accept	Verbal	Likelihood of accepting each offer
6	Does people's reliance on novices depend on how similar the novice's experience is to the decision maker's anticipated experience?	Whether the novice is similar or not	Booking a flight ticket	Numeric	Likelihood of booking a flight on the airline

each domain, participants then evaluated to what extent each of the two groups (everyday people/peers and critics/experts) matched eight distinct adjectives (relatable, approachable, trustworthy, supportive, collaborative, credible, confident, and objective), all on 7-point scales (1="Not at all", 7="Very much so").[6]

In the *response* condition, participants considered to what extent recent experience in the domain or the ability to synthesize relevant data to the domain was important when making a decision for each domain. For example, the event space domain text said (emphasis in original): "Imagine you're looking to find **an event space for an office holiday party** and are trying to determine **which event space to book**. To what extent is *recent experience with the event space* or *the ability to synthesize information and data about event spaces* important when determining **which event space to book**?" For each domain, participants responded on a scale from 1 ("Recent experience is definitely more important") to 9 ("Synthesizing information and data is definitely more important").

3.2. Analysis and Results

Correlation between choice and response. We hypothesized that there would be a significant, positive correlation between choice and response; for domains that participants in the *choice* condition indicate a preference for experts, participants in the *response* condition should indicate that synthesis of data is more important. To test this, we calculated (x) the mean reported importance of synthesizing data (over direct experience) and (y) the proportion of participants choosing to hear from experts in each domain. Then, we calculated the correlation between these mean responses. We found a significant, positive correlation overall (r = 0.966, b = 0.261, SE = 0.025, $t(8)$ = 10.501, p < 0.001; see Fig. 1). Notably, this correlation is high in part due to categorical differences between stimuli. We also conducted the same correlation on solely the domains we *a priori* predicted to be opinions from direct experience (e.g., craft beer selection, work shirt selection, event space for a work event selection, restaurant for lunch selection, and furniture for an office selection) and solely on the domains we *a priori* predicted to be opinions from data synthesis and extrapolation (e.g., house listing price, investment decision, job quitting rate prediction, number of units sold by a company prediction, sales by a given sales team prediction). For opinions we predicted as being based on direct experience, there was a smaller correlation (r = 0.839, b = 0.095, SE = 0.036, $t(3)$ = 2.671, p = 0.076); a similar pattern emerged for opinions we predicted as being based on data synthesis and extrapolation (r = 0.647, b = 0.079, SE = 0.054, $t(3)$ = 1.469, p = 0.238).

Choice responses. Next, we examined the *choice* condition responses in particular. Across domains, participants relied equally on

[6] These adjectives were chosen somewhat ad-hoc, as this question about which characteristics people think align more with experts and novices was more exploratory.

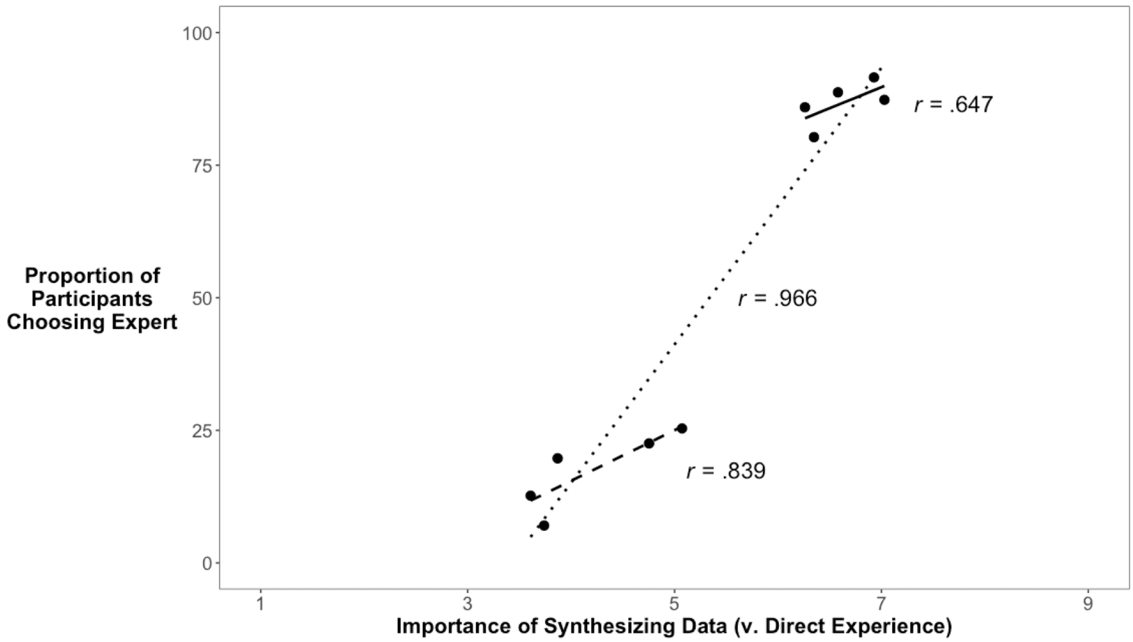

Fig. 1. Note: The dotted line represents the overall correlation between participants' rated importance of synthesizing data over experience by domain and choice of expert/critic. The dashed line represents this correlation within domains where choice of expert was below 50%, and the solid line represents this correlation in the opposite group of domains.

experts (52.1%) and novices (47.9%; $\chi^2(1) = 0.552$, $p = 0.457$, $h = 0.042$). However, we also tested whether participants were more likely to select novices for domains we categorized *a priori* as from direct experience, and experts for domains we categorized *a priori* as from data.[7] Using logistic regression to regress choice on an indicator for opinion from data and clustering standard errors by participant, we found that participants were more likely to choose experts for opinions from data (86.8%; b = 3.433, SE = 0.303, $z = 11.333$, $p < 0.001$, OR = 30.969).

Adjectives for each group. Next, we tested whether participants in the *choice* condition (as participants in the *response* condition did not respond to these questions) judged novices and experts differently on a variety of adjectives. Fig. 2 shows the mean response for each group and adjective, and Supplementary Materials A provide exact descriptive and inferential statistics. Notably, participants indicated that everyday people/peers are more relatable, approachable, supportive, and collaborative, while they found critics/experts to be more credible, confident, and objective (all *ps* < 0.001). Participants evaluated peers and experts as similarly trustworthy ($p = 0.400$).

3.3. Discussion

Study 1 shows that there is a correlation between people's choice of hearing from an expert or novice and the extent to which people value direct experience or synthesis of data; these initial results support our conjecture that people rely more on novices for opinions from direct experience (H_1) and experts for opinions from data (H_2). We also found that people were more likely to select novices for opinions from direct experience, and experts for opinions from data. Lastly, we found that people describe novices and experts differently.

Importantly, this study suggests that people choose experts (or novices) more for advice in certain domains. However, we are also (and mainly) interested in the extent to which people rely on these two groups given *how advice is formed*. Thus, Studies 2–5 test reliance on advice from each group, depending on the advice-generation process.

4. Study 2

Study 1 provided an initial investigation into people's preference for novice and expert opinions by asking for an explicit preference for one group or the other. While people may choose to seek out opinions from one group or another (e.g., searching for critic reviews of a movie), they are often—and increasingly—exposed to opinions from both groups (e.g., online via the websites for Rotten Tomatoes, Difford's Guide, etc.). Study 2 tested the latter case by showing people opinions from both sources for the probability of an outcome occurring and asking them to provide a likelihood judgment of their own. We tested whether people relied more on novices for opinions from direct experience (again product opinions in this study), and on experts for opinions from data (predictions of future events in this study).

4.1. Method

Participants. We preregistered to recruit 500 participants online from Connect by CloudResearch. Because some participants provided responses but did not submit a completion code for payment and completed the survey more than once, we wound up collecting data from 505 participants. Following our preregistration, we removed all observations from 2 participants with duplicated IP addresses or IDs and from 4 participants who did not submit a completion code for payment. We also necessarily removed observations from 4 participants who did not complete the dependent variable. Our final sample comprised 498 participants ($M_{Age} = 39.09$, 49.40% male, 50.60% female).

Procedure and design. After agreeing to the consent form, participants read that they would see pairs of opinions for six different contexts, and that these opinions were from experts, or "people with expertise in that context" and everyday people, or "people who do not have a particular expertise in the area." Then, participants saw opinions for six domains in a random order (leaving us with 2,988 observations in total). A participant's six domains were randomly selected from the

[7] Importantly, our *a priori* judgments match on to response from participants in the *response* condition; the 5 domains for which the *response* participants evaluated experience as being more important were the 5 domains we predicted were based on experience.

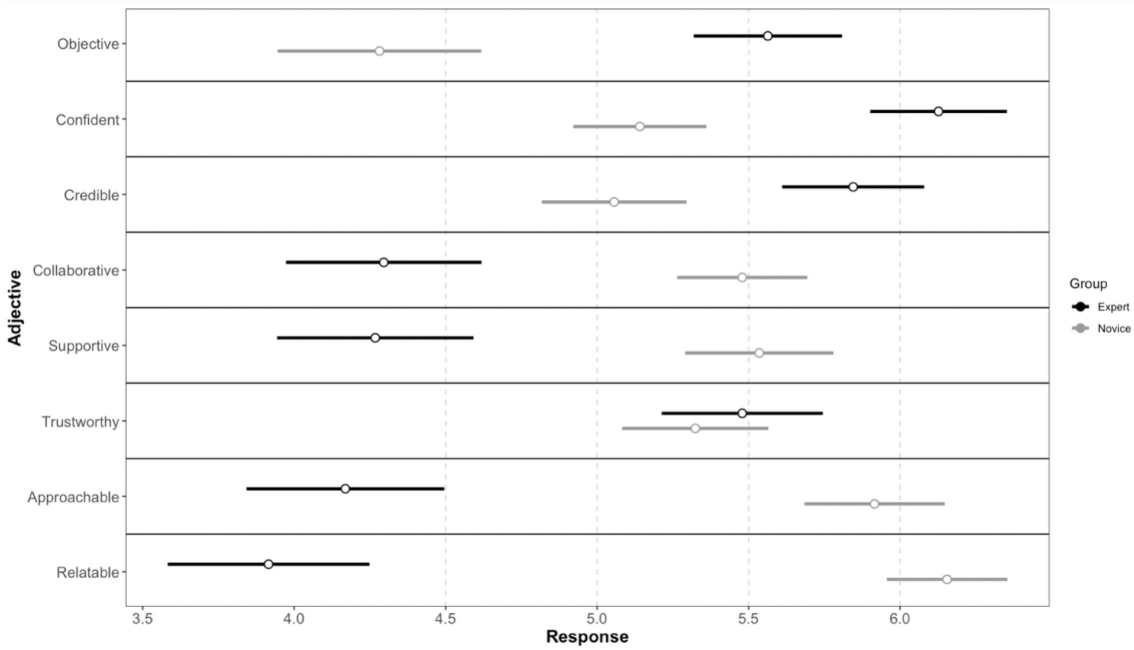

Fig. 2. Note: Horizontal lines represent 95% confidence intervals.

following eight: (ratings for) televisions, child's car seats, and craft beer, and (predictions of) hockey team wins, stock returns, apartment prices, snowfall, and percentage of votes for a political candidate. For each domain, participants read a brief description of the context (e.g., "Imagine the numbers below are predictions of how many games the Crimson Stallions, a hockey team, will win in their 2024–2025 season. There are 50 games in the Crimson Stallion's season."). They also saw a table with average numerical opinion and sample size for each of the two groups (see Fig. 3 for an example). The opinions shown for each group was randomly and independently drawn from a uniform distribution; we used different ranges for the uniform distribution for different domains. For each domain, participants answered a dependent variable question designed to measure how likely they thought the outcome was (see Table 2 for details by domain).

4.2. Analysis and Results

To test whether participants relied more on novices or experts for opinions generated from direct experience (i.e., product evaluations) or opinions generated from data (i.e., future predictions), we regressed likelihood on (1) the expert opinion shown minus the novice opinion shown, (2) an indicator for product opinion domains (coded as 0.5 for product domains and as –0.5 for future prediction domains), (3) the interaction of (1) and (2), and (4) fixed effects for domain. We also clustered standard errors by participant. We focus on the interaction between the expert minus novice opinion and product opinion indicator, because it signifies whether participants relied on experts and novices differently for product (i.e., opinion from direct experience) versus future prediction (i.e., opinion from data) domains. There was a significant interaction between the difference in expert and novice opinions and the product domains indicator (b = –.083, SE = 0.017, $t(497) = -4.808$, $p < 0.001$, $\eta_p^2 = 0.009$), suggesting that participants relied on novice and expert opinions differently in different domains. This regression also yielded a significant effect of the expert opinion minus novice opinion (b = –.041, SE = 0.009, $t(497) = -4.803$, $p < 0.001$, $\eta_p^2 = 0.001$) and a significant effect of product opinion domains (b = –1.316, SE = 0.138, $t(497) = -9.502$, $p < 0.001$, $\eta_p^2 = 0.02$).

To explore the interaction, we first re-ran the main regression with an indicator that was 0 for future prediction domains and 1 for product domains. We can then examine the expert opinion minus novice opinion variable to determine whether people rely more on experts or novices for future prediction domains (i.e., when the indicator is equal to 0). There was a significant, positive effect of the expert opinion minus novice opinion, indicating that for predictions of the future, when expert opinions increased, participants' likelihood responses were higher (e.g., more favorable; b = 0.00003, SE = 0.00002, $t(497) = 2.245$, $p = 0.025$, $\eta_p^2 = 0.001$). Then, we re-ran this regression with an indicator that was 0 for product domains and 1 for future prediction domains to explore the effect of the expert opinion minus novice opinion variable on likelihood for product domains. A significant, negative effect of the expert opinion minus novice opinion in this model suggested that participants' likelihood responses were lower when expert opinions were higher (b = –.083, SE = 0.017, $t(497) = -4.808$, $p < 0.001$, $\eta_p^2 = 0.009$).[8]

4.3. Discussion

Study 2 shows that when people view numerical advice from both novices and experts, they rely more on the former for advice assumed to be generated from direct experience (in line with H_1) and more on the latter for advice generated from data (in line with H_2). Thus, this study builds on Study 1 by showing that our hypotheses emerge both (1) in advice reliance, rather than only selection of advisor, and (2) for numerical advice. Further, this study shows our anticipated pattern of results across a variety of new products not tested in Study 1. Taken together, our results extend the generalizability of the results found in Study 1.

A notable limitation of Study 2 (and Study 1) arises from the fact that we manipulate opinion generation through manipulating domain. As a result, our manipulation of opinion generation is (i) assumed—we do not explicitly tell participants how the opinions they observed were generated—and (ii) confounded with whether opinions are reflective or predictive. The fact that our manipulation of opinion generation is assumed means that our evidence supporting H_1 and H_2 comes from data that are illustrative of reality, but imperfectly connected to those hypotheses themselves. The confound of prediction and reflection with

[8] Curious readers can find results by domain in Supplementary Materials B.

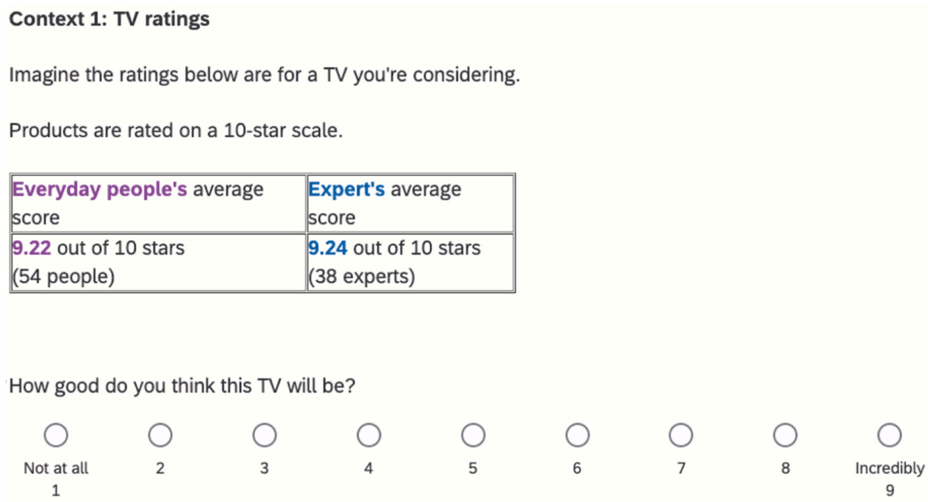

Fig. 3. Note: This figure shows an example of stimuli from Study 2.

Table 2
Stimuli for Study 2 by domain.

Type of opinion	Domain	Information shown	Likelihood question wording (9-pt scale)	Range of opinions shown	Range of number of novices and experts shown
Opinion from data	Sports	Imagine the numbers below are predictions of how likely (0% to 100%) it is that the Crimson Stallions, a hockey team, will make the playoffs.	How successful do you think the Crimson Stallions will be this season?	0 to 50	Novices: 15 to 300 Experts: 2 to 40
	Stocks	Imagine the numbers below are predictions of how likely (0% to 100%) it is that Orion Data Services's stock will grow in the next month.	From 0% to 100%, how likely do you think it is that Orion Data Service's stock will grow in the next month?	0.00% to 15.00%	
	Apartment	Imagine there is a large city called Maplewood. The numbers below are predictions of how likely (0% to 100%) it is that a specific 2-bedroom apartment in Maplewood will sell in the next month.	From 0% to 100%, how likely do you think it is that a specific 2-bedroom apartment in Maplewood will sell in the next month?	$1,500 to $15,000	
	Snowfall	Imagine there is a town called Oak Ridge. The numbers below are predictions of how likely (0% to 100%) it is that Oak Ridge will get at least 25 in. of snow this winter.	From 0% to 100%, how likely do you think it is that Oak Ridge will get at least 25 in. of snow this winter?	0.00 to 75.00 in.	
	Politics	Imagine there is an election this year for a state representative. The numbers below are predictions of how likely (0% to 100%) it is that Joe Johnson will win.	From 0% to 100%, how likely do you think it is that Joe Johnson will win?	0.00% to 100.00%	
Opinion from direct experience	TV ratings	Imagine the ratings below are for a TV you're considering.	How good do you think this TV will be?	1.00 to 10.00 stars	
	Car seat ratings	Imagine the ratings below are for a child's car seat you're considering.	How good do you think this car seat will be?		
	Craft beer ratings	Imagine the ratings below are for a craft beer you're considering.	How good do you think this craft beer will be?		

advice generation is more concerning. Though in reality, it may be the case that many domains in which opinions are commonly created through direct experience (data) are reflective (predictive), we believe this to be a correlate, and not necessarily the driving force of this effect. To test whether this is the case—whether advice generation drives reliance on experts and novices across domain and scope—we designed Studies 3, 4, and 5.

5. Study 3

Our main conjecture is that people rely on novices for advice or opinions from direct experience, and experts for advice or opinions from data synthesis and extrapolation. Studies 1–2 manipulate opinion type by changing domain. In contrast, Study 3 holds domain constant and simply manipulates whether the advice novices and experts give is generated by direct experience or synthesis and extrapolation of data. Thus, Study 3 provides a more direct test of whether opinion type affects reliance on novices and experts.

5.1. Method

Participants. We recruited online participants from Prolific. Using a pre-registered interim analysis design (PRIAD; André and Reinholtz 2024), we preregistered a sample size of 1,200 participants with two interim analyses at 396 and 792 participants. Because our p-value of interest in the second interim analysis was below the cutoff specified by our PRIAD ($p < 0.02199$), we only collected 792 participants. Because some participants provided responses but did not submit a completion code for payment and completed the survey more than once, we wound up collecting data from 871 participants. Following our preregistration, we removed data from 4 duplicate participants and data from 7 participants whose ID was not approved on the Prolific platform. We also necessarily removed data from 78 participants who did not complete the dependent variable. Our final sample comprised 788 participants and

4,728 observations ($M_{Age} = 40.22$, 40.23% male, 59.52% female, 0.25% prefer not to say).

Procedure and design. This study took the form of a 3 (domain: attending a hockey game, going skiing, or watching a movie) × 2 (opinion generation condition: direct experience or data) fully within-subjects design. Thus, there were six stimuli replicates in this study (e.g., two versions of each of the three domains), and all participants saw all six versions.

In particular, participants first read that they would see opinions from experts and everyday people predicting the extent to which other people would enjoy three different domains, and that they would read about each domain twice during the study.[9] Participants then saw opinions for each of the six possible domain-condition combinations in random order. For each combination, participants imagined attending a game played by a given hockey team, visiting a ski hill, and watching a movie, and read that the experts and novices providing opinions both generated their opinions in the same way. In particular, in the "direct experience" combination (which represented three of the six combinations viewed), we specified that both the experts and novices relied on their direct experience to generate their opinions. In the "data" combination (which represented the other three of the six combinations viewed), we specified that both the experts and novices relied on data about the given domain to generate their opinions (see Table 3 for an example).

To ensure participants were reading the stimuli manipulating opinion generation, we included an attention check question asking about the content participants read earlier on the page (e.g., whether the opinions were from novices and experts who had directly experienced the focal domain). For each of the six combinations, both groups (e.g.., novices and experts) always gave opinions on a 0–100% scale, indicating the percentage of people in that group who thought others would enjoy the experience. Opinions from each group were selected independently from random uniform distributions ranging from 0% to 100%. However, we enforced a difference in opinion between 10% and 30%, such that both opinions were resampled from those uniform distributions until this had been met. On the next page, participants saw the same explanation of the opinion generation process, opinions, and domain information, and answered our main dependent variable question, which asked how enjoyable participants thought the domain (e.g., attending the hockey game) would be on a 9-point scale.

Therefore, all participants in this study made six evaluations of their anticipated enjoyment from different stimuli. Three evaluations were made after observing opinions generated from direct experience from both experts and novices, and three after observing opinions generated from data from both experts and novices. These three evaluations were made for enjoyment of attending a hockey game, visiting a ski hill, and watching a movie in both opinion generation conditions. For each evaluation, we observe the difference between expert and novice opinions, which is our main independent variable. We anticipate that—across domains—expert opinions will be relied upon when all opinions are generated from data, and novice opinions will be relied upon when all opinions are generated through direct experience.

5.2. Analysis and Results

To test whether participants rely more on novice's opinions from direct experience, but more on experts for opinions generated from data, we regressed participants' reported anticipated enjoyability on (1) the expert opinion shown minus the novice opinion shown (mean-centered), (2) a contrast-coded indicator for the direct experience condition, (3) the interaction of (1) and (2), and (4) fixed effects for order.[10] There were no significant effects of the difference between expert and novice opinion (b = 0.0004, SE = 0.001, $t(787) = 0.282$, $p = 0.778$, $\eta_p^2 < 0.001$) nor the opinions from data condition (b = –.082, SE = 0.056, $t(787) = –1.458$, $p = 0.145$, $\eta_p^2 < 0.001$). Importantly, however, there was a significant interaction between the difference score and the indicator for opinions from data (b = 0.007, SE = 0.003, $t(787) = 2.633$, $p = 0.009$, $\eta_p^2 = 0.001$, see Fig. 4), indicating that participants relied more strongly on experts—through a more positive simple effect of expert minus novice opinion—when opinions were generated from data.

To explore the interaction, we first re-ran the main regression with an indicator that was 0 for opinions from direct experience and 1 for opinions from data. We can then examine the difference score to determine whether people rely more on experts or novices for opinions from direct experience (i.e., when the indicator is equal to 0). There was a non-significant, but directionally negative effect of the expert opinions minus novice opinions, indicating that for opinions from direct experience, as expert opinions increased relative to novice opinions, participants' reported enjoyability was lower (b = –.003, SE = 0.002, $t(787) = –1.601$, $p = 0.110$, $\eta_p^2 < 0.001$). Then, we re-ran this regression with an indicator that was 0 for opinions from data and 1 for opinions from direct experience to explore the effect of the difference score on reported enjoyability for opinions from data. Here, we found a positive effect of the expert opinions minus novice opinions, suggesting participants' enjoyability ratings were higher when expert opinions were relatively higher (b = 0.004, SE = 0.002, $t(787) = 2.035$, $p = 0.042$, $\eta_p^2 < 0.001$).[11]

5.3. Discussion

Study 3 holds domain constant and manipulates whether novices and experts generated their opinions via direct experience or data synthesis and extrapolation. It finds that people rely more on novices when opinions are generated via direct experience, and more on experts when opinions are generated via data synthesis and extrapolation. Indeed, this interaction between opinion generation and group occurred even though the domains tested here—hockey games, ski hills, and movies—were very experiential. Thus, while people might assume that opinions of these domains are generated from direct experience in the absence of other information (as shown in Studies 1 and 2), we find that when opinion providers clarify the way in which their opinions were generated, people's reliance on each group changes.

This study highlights a key practical implication of our work: if an opinion fits with people's perceptions of who they should rely on for a given opinion-generation process (i.e., a novice relied on direct experience or an expert relied on data), then the opinion-giver could highlight how they arrived at their opinion to increase people's reliance on it. This idea is further developed via an organizationally-relevant context in Study 4.

6. Study 4

Study 4 has four main goals. First, this study extends the findings of Study 3 to an organizationally-relevant context—deciding between two job offers—and where participants observe advice, rather than mere opinions, which adds important generalizability (Milyavsky & Gvili, 2024). In particular, across all conditions of Study 4, participants receive advice about which of two job offers to accept from a colleague or career counselor. However, we manipulate how the advisor explains that they

[9] There is a typo on this page in the survey; it says there are nine domains, when in fact there are six. All participants saw this typo, so we do not expect it to affect between-condition differences.

[10] There is a typo in our preregistration; instead of having "prediction from evaluation" as a regressor, we should have "opinion from data.".

[11] This p-value is statistically significant at the traditional level, but not at our PRIAD level of 0.02199.

Table 3
Example Stimuli Manipulating Opinion from Direct Experience Versus Data.

<table>
<tr><th>Opinion from Direct Experience Condition</th><th>Opinion from Data Condition</th></tr>
<tr>
<td>Imagine there is a ski hill called Ski Valley. All the people in each group below skied at Ski Valley at least once this season.

The numbers below represent what percentage of people in each group predict that other people will enjoy their experience going skiing at Ski Valley.

<table>
<tr><td>Expert's average prediction</td><td>Everyday people's average prediction</td></tr>
<tr><td>33% predict that other people will enjoy their experience</td><td>9% predict that other people will enjoy their experience</td></tr>
</table>
</td>
<td>Imagine there is a ski hill called Silver Peak. All the people in each group below did not ski at Silver Peak before. However, these people have reviewed information about the ski hill, like the weather conditions, business, etc.

The numbers below represent what percentage of people in each group predict that other people will enjoy their experience going skiing at Silver Peak.

<table>
<tr><td>Expert's average prediction</td><td>Everyday people's average prediction</td></tr>
<tr><td>64% predict that other people will enjoy their experience</td><td>38% predict that other people will enjoy their experience</td></tr>
</table>
</td>
</tr>
</table>

Note: This table shows example stimuli from the ski hill domain. We counterbalanced which condition was called "Ski Valley" and "Silver Peak" between-subjects. The wording was very similar for the two other domains we tested.

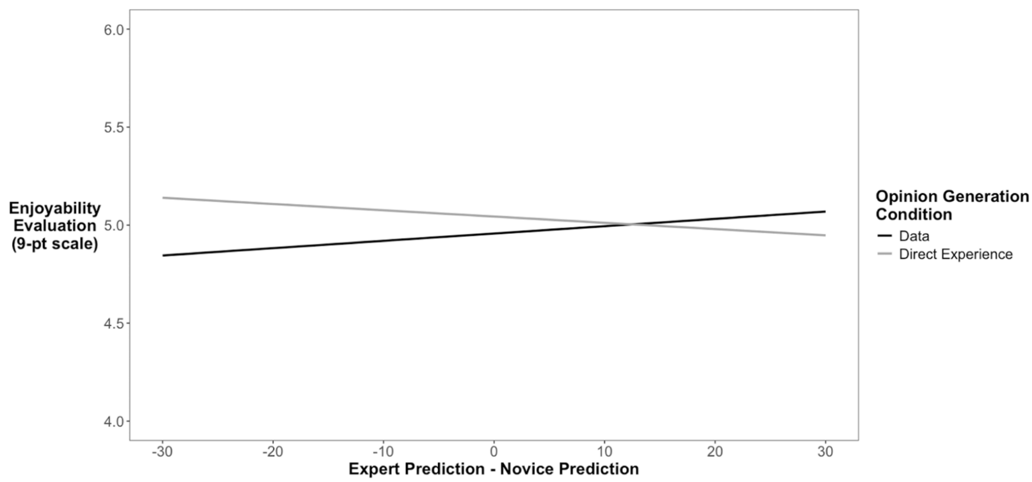

Fig. 4. *Note:* The slope of the line for the opinion from experience condition is negative, suggesting that as expert opinions increased relative to novice opinions, participants judged the focal activity to be less enjoyable. However, the slope of the line for the opinions from data condition is positive, suggesting that as expert opinions increased relative to novice opinions, participants evaluated the activity to be more enjoyable.

arrived at their advice, and predict that when the advice is formed from synthesizing and extrapolating from data, people will rely heavily on experts. But when the advice is formed from direct experience working with the companies, we expect people to rely on novices.

Second, this study also tests what happens when advice is derived from similar experience (e.g., working at a similar company) and observed experience (e.g., hearing from other people who work at the company). Similar and observed experience share similarities with both advice based on data and advice based on direct experience. Experience (rather than data) is still focal in the advice-generating process, which could mean novices are relied upon. However, because the experience is not direct, it requires more synthesis and extrapolation than direct experience—something that people may believe experts are better at. Because of this, we predict participants' reliance on experts and novices in these two conditions will fall in the middle of the direct experience and data conditions.

Third, while novices and experts in Studies 2 and 3 provided numeric advice, the novice and expert in Study 4 provide verbal advice (e.g., "My recommendation is to accept the offer from Vernon & Co. Consulting"), thus allowing us to test whether our findings are robust to verbal advice from both groups, which may be more common.

Fourth, previous research has highlighted that certain situational characteristics increase reliance on novices (or experts; Fadel et al., 2022). We argue for a distinct antecedent of whether people rely on advice: the fit between the advice-generation process and the expertise of the advisor. However, one may wonder whether our advice-generation manipulations simply change the characteristics people perceive of the situation. To rule out this possibility, Study 4 measures the perceived objectivity and commonness of the situation (e.g., choosing a job offer). If our results were only driven by characteristics of the situation dictating people's reliance on novices versus experts, then we would expect controlling for these characteristics to reduce our experimental condition manipulation to non-significance. However, if advice generation interacts with advisor expertise to affect how persuasive advice is (as we argue), accounting for these characteristics should not significantly change our findings.

6.1. Method

Participants. We recruited 1,600 online participants from Connect. Because some participants provided responses but did not submit a completion code for payment and completed the survey more than once, we collected data from 1,638 participants. Following our preregistration, we removed data from 7 participants whose ID was not approved on the Connect platform because they did not submit a completion code and 6 duplicate participants. We necessarily removed data from 29 participants who did not complete the dependent variable. Our final sample comprised 1,596 participants (M_{Age} = 40.554, 47.31% male, 52.19% female, 0.06% intersex, 0.44% prefer not to say).

Procedure and design. After agreeing to the consent form and successfully completing a reCAPTCHA task to ensure the participant was a human, participants read that they were considering two job offers and sought advice about which offer to accept from two people: a colleague and a professional career counselor. Participants read that both the colleague and career counselor were giving advice for free.

Then, participants read advice from the novice and career counselor; the order of advice was counterbalanced between participants. For all participants, the friend and career counselor's advice disagreed, in that one advisor always recommended the opposite company from the other; we counterbalanced which advisor recommended which company. However, the content of the advice depended on experimental condition; participants were randomized to one condition in this 4-condition (advice formation: direct experience v. data v. observed experience v. similar experience) between-subjects design.

In particular, in the *direct experience* condition, both the career counselor and friend explained that they were "giving advice based solely on my experience with the two companies" and that they had worked at both companies. In the *observed experience* condition, both parties explained that they were "giving advice based solely on what I've seen from folks I know who work at these two places," while in the *similar experience* condition, both parties explained that they were "giving advice based solely on my experience at companies similar to these two." Both parties in all three conditions explained that they knew the day-to-day culture, workload, and growth paths of the companies from their direct, observed, or similar experience, respectively. In the *data* condition, participants read that both advisors were giving their recommendations "solely based on my evaluation of publicly available information about the two companies." Participants further read that the advisor could speak to the salary reports, employee satisfaction reports, and firm-based financial statements (see Table 4 for example stimuli).

To ensure participants read and understood the advice, they completed an attention check question before moving on in the survey. Then, participants saw the advice again, read instructions that stated that "if you say you're not likely to accept either job offer, then you're saying you'd continue looking for other jobs" and answered the two main dependent variable questions, which asked how likely they were to take an offer from each company (both on 9-point scales). Then, participants answered additional measures on the following two pages. On one page, participants indicated how similar they thought they were to the colleague and career counselor described (e.g., "My work experiences are likely similar to Jordan's experiences," each measured on a 9-point scale). On the other, participants indicated how (1) subjective or objective they thought choosing a job offer to accept was and (2) how commonly or uncommonly experienced choosing a job offer to accept is (both measured on 9-point scales).

6.2. Analysis and results

We predicted that participants would be more likely to rely on the career counselor's advice when company evaluations were based on data, and rely more on the novice's advice when company evaluations were based on direct experience. Because observed and similar experience are based on experience but still require extrapolating from observations or one's own, different experience to arrive at advice, we expect these conditions to fall in the middle of the data and direct

Table 4
Example Stimuli Manipulating Advice Across Conditions in Study 4.

Direct Experience Condition	**Data Condition**
First, **Dr. James, the Professional Career Counselor**, gives you their advice. They say: "I'm giving advice based solely on my experience with the two companies. Since I've worked with both companies, I can speak to the day-to-day culture, workload, and growth paths. My recommendation is to accept the offer from ***Vernon & Co. Consulting***." Next, **Jordan, your work colleague**, gives you their advice. They say: "My recommendation is solely based on my experience with the two companies. Having worked with both companies, I can speak to the day-to-day culture, workload, and growth paths. I recommend you accept the offer from ***Stratus Edge Solutions***."	First, **Jordan, your work colleague**, gives you their advice. They say: "My recommendation is solely based on my evaluation of publicly available information about the two companies. Having reviewed information about both companies, I can speak to the salary reports, employee satisfaction reports, and firm-based financial statements. I recommend you accept the offer from ***Stratus Edge Solutions***." Next, **Dr. James, the Professional Career Counselor**, gives you their advice. They say: "I'm giving advice based solely on my evaluation of publicly available information about the two companies. Since I've reviewed information about both companies, I can speak to the salary reports, employee satisfaction reports, and firm-based financial statements. My recommendation is to accept the offer from ***Vernon & Co. Consulting***."
Observed Experience Condition	**Similar Experience Condition**
First, **Dr. James, the Professional Career Counselor**, gives you their advice. They say: "My recommendation is solely based on what I've observed from people I know who work at these companies. Knowing people who have worked at both companies, I can speak to the day-to-day culture, workload, and growth paths. I recommend you accept the offer from ***Vernon & Co. Consulting***." Next, **Jordan, your work colleague**, gives you their advice. They say: "I'm giving advice based solely on what I've seen from folks I know who work at these two places. Since I know people who have worked with both companies, I can speak to the day-to-day culture, workload, and growth paths. My recommendation is to accept the offer from ***Stratus Edge Solutions***."	First, **Dr. Jordan, the Professional Career Counselor**, gives you their advice. They say: "My recommendation is solely based on my experience working at companies like these two companies. Having had experience at similar companies, I can speak to the day-to-day culture, workload, and growth paths. I recommend you accept the offer from ***Stratus Edge Solutions***." Next, **James, your work colleague**, gives you their advice. They say: "I'm giving advice based solely on my experience at companies similar to these two. Since I've worked with similar companies, I can speak to the day-to-day culture, workload, and growth paths. My recommendation is to accept the offer from ***Vernon & Co. Consulting***."

Note: This table shows example stimuli. Notably, as shown here, we counterbalanced which company each advisor recommended, the order of advice, and the name of the expert and novice, all in a between-subjects manner.

experience conditions.

We preregistered to calculate a difference score between the likelihoods of accepting the offer at the company recommended by the expert and novice, respectively. This difference is positive if a participant is more likely to take the offer from the expert-recommended company. We then regressed this difference on an indicator for the *direct experience* condition, the *observed experience* condition, the *similar experience* condition, and fixed effects for the order of which advisor's advice was shown first. Because this includes indicators for all but the *data* condition, all effects estimate the difference from the *data* condition. Compared to the *data* condition (M = 1.470, SD = 2.540), the difference score was significantly smaller in the *direct experience* condition (M = –0.330, SD = 3.042; b = –1.799, SE = 0.201, $t(1591) = -8.934$, $p < 0.001$, $d = -.64$), the *observed experience* condition (M = 0.489, SD = 2.832; b = –0.980, SE = 0.202, $t(1591) = -4.856$, $p < 0.001$, $d = -.37$), and the *similar experience* condition (M = 0.255, SD = 2.951; b = –1.213, SE = 0.202, $t(1591) = -5.993$, $p < 0.001$, $d = -.44$; see Fig. 5 for a graph of the means).

Using a similar regression with indicators for the *data* condition, the *observed experience* condition, and the *similar experience* condition—such that all effects became relative to the *direct experience* condition, we also found that the difference score in the *observed experience* condition (b = 0.819, SE = 0.201, $t(1591) = 4.070$, $p < 0.001$, $d = 0.28$) and *similar experience* condition (b = 0.586, SE = 0.202, $t(1591) = 2.908$, $p = 0.004$, $d = 0.20$) were significantly higher than the *direct experience* condition. There was no significant difference between the *observed experience* and *similar experience* conditions (b = 0.233, SE = 0.202, $t(1591) = 1.151$, $p = 0.250$, $d = 0.08$).[12]

We can also calculate whether the difference score for each condition is significantly different from 0 using a one-sided *t*-test. If the difference score for a given condition is not significantly different from 0, it suggests participants are on average indifferent between accepting the job the career counselor recommends and accepting the job the colleague recommends. We found that the mean in the *direct experience* condition was significantly smaller than zero ($t(402) = -2.178$, $p = 0.030$, $d = -.11$), suggesting that participants in this condition relied more on advice from their colleague than the career counselor. The difference score in the *data* ($t(397) = 11.545$, $p < 0.001$, $d = 0.48$) and *observed experience* ($t(398) = 3.447$, $p < 0.001$, $d = 0.16$) conditions were significantly larger than zero, suggesting participants relied more on the career counselor's advice than their colleague's advice. In the *similar experience* condition, the mean was marginally significantly larger than zero ($t(395) = 1.720$, $p = 0.086$, $d = 0.08$).

We also collected perceived similarity to the colleague and career counselor. We predicted that participants would think their colleague would have more similar experiences to themselves than the career counselor, and indeed found that to be the case (colleague: M = 6.711, SD = 1.645; career counselor: M = 3.807, SD = 1.781; $t(1595) = 42.648$, $p < 0.001$, $d = 1.694$). Results suggest that this perceived similarity explains participants' reliance on novices for advice from direct experience. Specifically, we simplified our data to only include the direct experience and data conditions, and then interacted the relative similarity of novices to experts (novice similarity, minus expert similarity) with a dummy code for condition (0 = direct experience, 1 = data). In this model, there was a significant simple effect in the direct experience condition of perceived similarity of novices on likelihood of taking the job at the expert-recommended company (b = –0.437, SE = 0.051, $t(796) = -8.601$, $p < 0.001$, $\eta_p^2 = 0.07$), such that higher perceived similarity to novices led to lower stated likelihood to follow the expert's advice. There was also a significant interaction of novice's relative similarity and condition (b = 0.327, SE = 0.071, $t(796) = 4.577$, $p < 0.001$, $\eta_p^2 = 0.03$), such that the effect of advice generation on reliance on novices and experts was moderated by relative similarity of novices—when novices were perceived to be relatively more similar, the effect of advice generation on choice was more pronounced.

Lastly, one possible explanation for our results is that the advice manipulations simply change the perceived characteristics of the situation, which has been shown to change reliance on novices and experts (Fadel et al., 2022). If this were true, then including participants' perceived situational characteristics in the regression (along with our condition indicators) should lead the condition indicators to no longer be significant. We do not find this result. While the subjectivity/objectivity of the job choice situation did significantly predict the difference score (b = 0.133, SE = 0.034, $t(1590) = 3.966$, $p < 0.001$, $\eta_p^2 = 0.010$), including it in each of our preregistered regressions did not meaningfully change our results (see Supplementary Materials C for full regression results). Participants' perceived commonness of choosing a job did not significantly predict the difference score ($p > 0.9$), and including this measure in each of our preregistered regressions did not meaningfully change our results either. Thus, these results suggest it is unlikely that our findings are simply driven by our advice generation manipulations changing people's perceived characteristics of the situation (and therefore their reliance on novices and experts). We further rule out this possibility by manipulating situational characteristics in Study 5.

6.3. Discussion

Study 4 shows that people rely more on experts when advice is derived from data, and rely on experts less when advice is derived from direct experience. Even in a new domain (e.g., job offer) with verbal (rather than numeric) advice, we still find that people rely more on experts for advice formed from data synthesis and extrapolation, rather than for advice formed from direct experience. Additionally, we find initial evidence of our mechanism: that people rely more on novices for advice from direct experience because they think novices have more similar experiences to those they expect to have when compared to experts.

Importantly, this study also investigated two other ways of arriving at advice: from similar experience and observed experience. As we predicted, these two conditions were somewhere in between the results from our direct experience and data conditions. This is likely because similar and observed experience have elements of advice formation from both direct experience and data: the source of advice is still experience, but since it is not direct experience, more synthesis and extrapolation is required to arrive at advice. In this study, both conditions yielded significantly different means from the direct experience and data conditions, meaning that they did not resemble either condition, and instead something in the middle.

In other domains, people's baseline reliance on novices or experts might be different. In such cases, we expect the differences *between* the four conditions we test to be similar. However, we suspect the means of all four conditions would change (by a similar extent in each condition).

Lastly, this study tested whether situational characteristics measured (e.g., subjectivity) drove the patterns of results we find, rather than our advice generation manipulations. Our initial results suggest they do not, as including a measure of perceived subjectivity (and of perceived commonness of the situations) does not meaningfully change our results.

7. Study 5

Study 4 found that the advice-generation manipulations did not seem to act as a proxy for the situational characteristics that Fadel et al. (2022) suggest influence reliance on novices and experts. Study 5 sought to further address this possibility by directly manipulating situational characteristics using the same job choice paradigm as in Study 4. Because we found that participants' perceived subjectivity/objectivity

[12] We replicate these findings in Study S1, an experiment that describes the novice as a friend, rather than colleague, and uses a 2-cell design comparing the data and direct experience conditions.

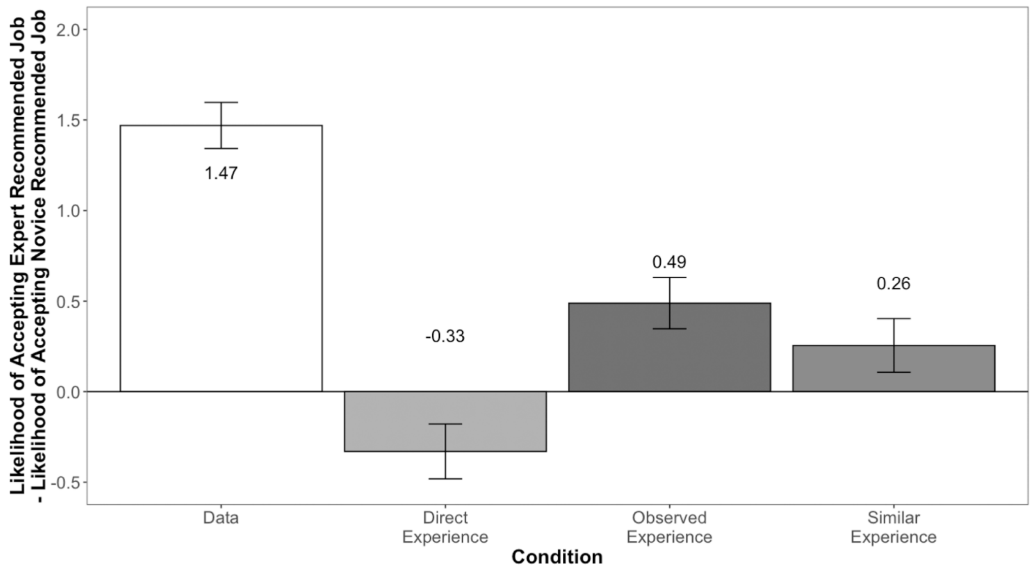

Fig. 5. *Note:* Error bars represent +/- 1 standard error.

of a job choice significantly predicted job choice in Study 4, while perceived commonness of the situation did not, Study 5 directly manipulates only how subjective or objective the job choice decision is perceived to be. We suggest that the advice generation process is a novel, distinct antecedent of reliance on expert or novice advice. If this is the case, then manipulating situational characteristics will have no significant effect on the strength of the advice generation manipulation. However, if the advice generation process is acting as a proxy to manipulate situational characteristics, then manipulating how subjective or objective the job choice decision is should change the strength of the advice generation manipulation.

7.1. Method

Participants. We recruited 1,200 online participants from Connect. Because some participants provided responses but did not submit a completion code for payment and completed the survey more than once, we collected data from 1,199 participants. Following our preregistration, we removed data from 2 participants whose ID was not approved on the Connect platform because they did not submit a completion code. We necessarily removed data from 28 participants who did not complete the dependent variable. Our final sample comprised 1,199 participants ($M_{Age} = 40.377$, 44.20% male, 55.55% female, 0.25% prefer not to say).

Procedure and design. This study was identical to Study 4, with two notable differences. First, participants were randomized to a condition in this 2(advice formation: direct experience v. data) x 3(situation characteristic: subjective v. objective v. none) between-subjects design. When introduced to the situation of deciding between two job offers, participants in the *subjective situation* (*objective situation*) condition read that a job offer is very subjective (objective), meaning "it depends on characteristics that vary greatly from person to person" ("it depends on characteristics that do not vary greatly from person to person"). Participants in these two conditions had to answer an attention check question about this information before continuing in the study, to ensure they read and understood the information. Participants in the *none* condition did not read any additional information about the situation.

Second, we did not include any additional questions to measure perceived similarity or perceived characteristics of the situation in this study.

7.2. Analysis and results

We predicted that participants would be more likely to rely on the career counselor's advice when company evaluations were based on data, and rely more on the novice's advice when company evaluations were based on direct experience. We also predicted that this difference would not be significantly moderated by framing the problem of choosing a job as subjective or objective.

As in Study 4, we preregistered to calculate a difference score between the likelihoods of accepting the offer at the company recommended by the expert and novice, respectively. We then regressed this difference on an indicator for the *direct experience* condition, the *subjective* condition, the *objective* condition, the interaction of the *direct experience* and *subjective* condition indicators, the interaction of the *direct experience* and *objective* condition indicators, and fixed effects for the order of which advisor's advice was shown first. Across all three characteristic manipulation conditions, we found that participants in the *direct experience* condition were more likely to accept the offer recommended by their colleague compared to those in the *data* condition (all $ps < 0.001$, see Supplementary Materials D for full regression output and Fig. 6 for means by condition). Further, the interaction between the *direct experience* indicator and the *subjective* condition indicator was not significant (b = 0.153, SE = 0.390, $t(1192) = 0.392$, $p = 0.695$, $\eta_p^2 < 0.001$), nor was the interaction between the *direct experience* indicator and the *objective* condition indicator (b = –.023, SE = 0.390, $t(1192) = -0.059$, $p = 0.953$, $\eta_p^2 < 0.010$).

7.3. Discussion

Study 5 sought to rule out the alternative explanation that manipulating advice formation simply changes people's perceived characteristics of the situation, which in turn affects their reliance on novices and experts (Fadel et al., 2022). To do so, it manipulated a situational characteristic (subjectivity) that significantly predicted the outcome measure in Study 4. We did not find that manipulating how subjective or objective a situation is perceived moderated our previously documented effects.

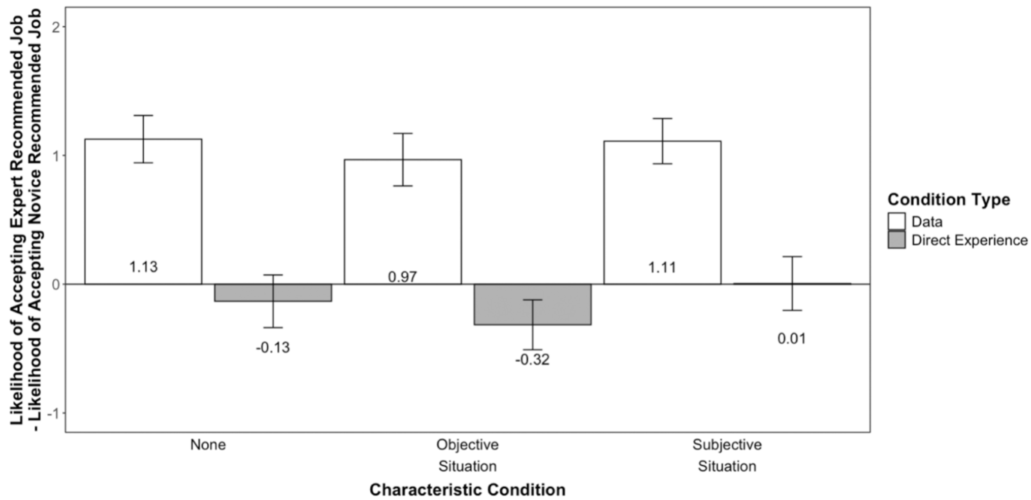

Fig. 6. *Note:* Error bars represent +/- 1 standard error.

8. Study 6

Our prediction is that people rely on novices more when advice is formed from direct experience because they think novices will experience a situation similarly to how they will. In Study 6, we test this conjecture by manipulating situational similarity directly. In particular, all participants read that they are looking to buy an economy ticket for a flight; in one condition, the novice giving advice flies economy class, and in another, the novice giving advice flies business class.

Notably, like Studies 4 and 5, Study 6 also does not explicitly label the novice and expert as such; instead, it describes someone who has limited domain experience and flies for their own benefit (e.g., someone who flies from time to time), and someone who has relatively deeper domain experience and flies to form advice (e.g., a journalist, travel industry analyst, or travel industry blogger). We use these less-specific labels to mimic labels people might see in real-world decisions, and thus test the generalizability of our findings.

8.1. Method

Participants. Using a pre-registered interim analysis design (PRIAD; André and Reinholtz 2024), we preregistered a sample size of 1,200 participants with one interim analysis at 600 participants. Because our p-value of interest in the second interim analysis was below the cutoff specified by our PRIAD ($p < 0.02939$), we only collected data from 600 participants. Following our preregistration, we removed data from 17 participants whose ID was not submitted for payment on the Connect platform. Our final sample comprised 600 participants ($M_{Age} = 38.342$, 41.50% male, 57.33% female, 0.33% intersex, 0.83% prefer not to say).

Procedure and design. This study took the form of a 2-condition (novice similarity: similar v. dissimilar) between-subjects design. First, participants agreed to the consent form and completed a reCAPTCHA to ensure they were human. Then, all participants read that they were looking to buy an economy ticket for a flight, and were considering two airlines that fly into their destination airport. Participants answered an attention check question to ensure they correctly read what class ticket they were interested in buying. Then, participants viewed two star ratings for the airline they were considering, one from an expert (described as a journalist, industry analyst, or blogger, randomly determined between-subject) and one from a novice (described as someone who flies from time to time, and usually books an economy-class or business-class ticket for all subjects).

In the *similar* condition, participants read that the novice usually booked an economy-class ticket, while in the *dissimilar* condition, participants read that the novice usually booked a business-class ticket. The order of opinions presented was randomized, and each person's opinion was shown on a separate page. The expert always rated the airline four stars, while the novice always rated the airline two stars (both out of five stars). Participants then responded to our primary dependent variable, asking them how likely they would be to book a flight on this airline (evaluated on a 9-point scale).

Lastly, we included several exploratory questions, and a series of debriefing questions to test for possible demand in the study. Participants indicated to what extent they think they will have a similar experience as the novice and expert, how often they fly on a commercial airline, which cabin they usually fly (e.g., economy or business), what they thought the purpose of the study was (free response, coded by GPT-5-nano version 2025–08-07 through the OpenAI API; GPT-5 System Card, 2025), why they think we showed opinions from two groups (free response, coded by GPT-5-nano through the OpenAI API), and whether they felt that we (as researchers) wanted them to rely on one group vs. another to make their choice. We report the results of these debrief questions fully in Supplementary Materials E. However, it is worth noting that GPT coded only 7 (1.2%) as guessing the purpose of the study fully, with this appearing very liberal upon inspection of those responses. No results below are meaningfully changed if we exclude those 7 responses, or the 101 (16.8%) that GPT coded as guessing the study purpose in part (Supplementary Materials E).

8.2. Analysis and results

First, we tested whether our manipulation was successful. Indeed, we found that participants in the *similar* condition thought the novice would have a more similar flight experience to themselves (M = 6.156, SD = 1.857) than those in the *dissimilar* condition (M = 4.138, SD = 2.149; $t(598) = 12.314$, $p < 0.001$, $d = 1.01$).

To test whether participants' likelihood of booking a ticket on the airline differed based on condition, we conducted a *t*-test. Participants in the *similar* condition were less likely to book the airline (M = 5.066, SD = 1.751) than those in the *dissimilar* condition (M = 5.933, SD = 1.551; $t(598) = -6.415$, $p < 0.001$, $d = -0.52$); given the novice always evaluated the airline unfavorably, this difference suggests that participants relied more on novices' unfavorable view of the airline in the *similar* condition. This result was consistent across the different types of experts we tested (see Table 5).

We also conducted several secondary analyses. First, we tested

Table 5
Robustness of Study 6 Results Across Expert Types.

Expert Type	Novice Similar Condition Mean (Standard Deviation)	Novice Dissimilar Condition Mean (Standard Deviation)	*t*-test results
A journalist who reports on travel for a well-known media outlet	5.277 (1.761)	6.000 (1.384)	$t(196) = -3.202$, $p = 0.002$, $d = -.46$
A professional blogger who runs a large travel blog and vlog	4.838 (1.682)	5.929 (1.698)	$t(196) = -4.541$, $p < 0.001$, $d = -.65$
An industry analyst who studies trends in aviation professionally	5.078 (1.795)	5.873 (1.565)	$t(202) = -3.368$, $p < 0.001$, $d = -.47$

whether participants' reported similarity to the novice predicted their likelihood of booking a ticket on the focal airline. We found a significant, negative relationship (b = –0.152, SE = 0.031, $t(598) = -4.968$, $p < 0.001$, $\eta_p^2 = 0.04$), suggesting that when people thought the novice was more similar to themselves, they were less likely to book the airline (because the novice evaluated it poorly).

We were also interested in whether the effect of the *dissimilar* condition on the likelihood of buying a flight ticket changed when controlling for either the frequency that participants report that they fly or whether they usually fly business or economy class. In both cases, the effect of the *dissimilar* condition was still significant (controlling for frequency of flying: b = 0.857, SE = 0.134, $t(596) = 6.390$, $p < 0.001$, $\eta_p^2 = 0.07$; controlling for usually flying business or economy: b = 0.851, SE = 0.135, $t(596) = 6.291$, $p < 0.001$, $\eta_p^2 = 0.06$). The interactions between condition and frequency of flying or class usually flown were not significant (*ps* > 0.700).

8.3. Discussion

Study 6 empirically demonstrated why people rely more on novices for advice from direct experience: because they think novices will have similar experiences to those they themselves will. When a novice is described as having a markedly dissimilar experience to the decision maker, participants relied significantly less on the novice for advice. This is consistent with the results from measured similarity in Study 4, where we observed a significant simple effect of perceived similarity within the direct experience condition, and where an interaction suggested there was a stronger effect of advice generation process when novices were deemed to have similar experiences. In this study, however, we observe this result when directly manipulating similarity of novices, allowing for a stronger causal argument.

9. General Discussion

In many settings, people seek and/or observe advice and opinions from novices and experts, relying on both groups to form a judgment. But whom do they rely *more* on, or are *more likely* to choose, and what affects this reliance? Six preregistered studies show that people rely more on and are more likely to seek experts for advice generated from data synthesis and extrapolation and novices for advice and opinions generated from direct, lived experience. This appears to be because people judge novices to have more similar experiences to what they will experience, but trust experts more to synthesize and extrapolate from data. This pattern occurs across many different domains (e.g., job choice, financial predictions, product opinions), and our effects emerge regardless of the labels we use for each group (e.g., critics vs. experts, everyday people vs. consumers vs. novices, no explicit label), whether the advice and opinions are numeric or verbal, whether the advice and opinions are given by one or many people representing each group, and whether the outcome of interest is choosing groups to hear from or judgments after being given advice and opinions from both groups.

Our findings offer several practical and theoretical contributions. Theoretically, we provide a generalizable framework to understand how people evaluate advice and opinions from novices and experts. In doing so, we build on research investigating advice taking (Blunden et al., 2019; Bonaccio & Dalal, 2006; Harvey & Fischer, 1997; Hofmann et al., 2009; Lee, 1997; Phillips, 1999; Sah et al., 2013; Schrah et al., 2006; Van Swol & Ludutsky, 2007; Yaniv, 2004), and show a novel antecedent of who people seek advice from: the advice-generation process. While previous research highlights why people value novices or experts for advice (Essig, 2024; Feng & MacGeorge, 2006; Harvey & Fischer, 1997; Lee, 1997; Price & Stone, 2004) or suggests situational characteristics drive reliance on an expert or novice (Fadel et al., 2022), our work provides a set of novel conditions under which people might seek out (Study 1) or rely upon (Studies 2–5) advice from one group or another. It also importantly demonstrates that these conditions are not limited to specific domains. Instead, the conditions are specific to how the advice was generated.

Practically, our results suggest that people's reliance on experts and novices may be malleable by highlighting how each group arrived at their advice and opinions. For instance, as shown in Studies 3–5, people rely more on certain groups if that group highlights how they arrived at the advice and it fits with people's perceptions of each group's strength (e.g., novices providing advice from direct experience, experts providing advice from data). Thus, experts can increase the persuasive appeal of their advice and opinions by highlighting the data they analyzed and extrapolated from to arrive at their advice. They should especially do this if people might assume, without any information on the advice-generation process, that direct experience was used to arrive at the advice (in which case people might be inclined to rely more on novices). For example, Studies 1 and 2 find that people rely more on novices in domains where people might assume direct experience was used to form the advice or opinion (e.g., product ratings, experiential settings). Experts can make their advice from data more persuasive in these domains by highlighting the data they used to arrive at their advice. Similarly, novices can make their advice in domains people usually assume rely on data to generate advice more compelling by highlighting the direct experience they had that shaped their advice.

9.1. Future directions

From our generalizable framework exploring when people rely on experts and novices, a number of interesting, follow-up questions emerge. In particular, we consider how the number of people advice or opinions are given to, the presence of one group's advice or opinion only, the expertise of the decision maker, the way in which the expert's advice is formed, whether people's decisions might be rational or not, the number of people making a judgment, and a situation in which people can learn over time might impact the results we demonstrated in this manuscript.

Studies 1–2 suggest that people assume that advice from certain domains is generated via direct experience or data. For instance, our results suggest people assume product ratings are formed from direct experience, while predictions of the future are formed via data analysis and extrapolation. Notably, these two categories of domains (e.g., product opinions and predictions of the future) differ in terms of both timing and whether advice is given for one person or many people. In particular, product ratings are often about summarizing a past experience, while predictions of the future make forward-looking suggestions.

Additionally, product ratings are often written first-hand, while future predictions forecast what a group of people will do (e.g., team members on a sports team, a collection of various people affecting stock prices, etc.). While these factors correlate with the domains tested in Studies 1 and 2, Studies 3 and 4 rule out the possibility that either of these factors is driving our pattern of results, since both studies keep timing and scope of advice and opinions constant across generation conditions. However, future research could explore how these factors affect advice reliance while holding advice-generation processes constant. This could be a fruitful avenue for future research, as it would further highlight novel differences in reliance on advice from novices and experts.

Additionally, we focus on contexts in which people view advice from both novices and experts in this manuscript. However, given there are real-world contexts in which people view advice from only one group or another, it could be useful to consider how these dynamics might play out in such settings. On the one hand, the relative strengths and weaknesses of novices and experts might be less salient with only one group displayed, which could dampen the effects we find. On the other hand, people might associate novices and experts strongly with certain characteristics (e.g., similar experiences or ability to synthesize and extrapolate from data), so the effects we demonstrate here could be similar or amplified. Future research could test this.

All our studies assume decision makers are novices, as most people are novices in many important domains. However, there are domains in which people have expertise, and it would be interesting to see how people's reliance on novices and experts differs when they are experts themselves. In particular, when someone is an expert, novices are no longer perceived to experience situations similarly to themselves. Instead, other experts are perceived to have similar experiences. Additionally, other experts can synthesize and extrapolate from data. Taken together, we hypothesize that experts would rely more on experts than novices across all domains and advice-generation processes, because the benefit of novices (e.g., perceived similarity and similar experiences) is no longer present. Future research can test whether this is the case.

Relatedly, how an expert arrives at their expertise could affect people's reliance on the expert. We argue that people think experts can synthesize and extrapolate from data, even if no information is provided to suggest this is the case (e.g., in our studies, experts are described vaguely, such as "people with expertise in that context"). But, if an expert encapsulates all characteristics of an expert but, for some reason, clearly cannot synthesize and extrapolate from data, people might rely less on them for advice generated from data. On the other hand, it is possible that people are somewhat agnostic as to how expertise is formed and the level of data synthesizing ability, so long as the expert encompasses key characteristics that people perceive experts should have.

Another potentially interesting question is whether differential reliance on novices and experts (as shown in this manuscript) is a mistake, or is a rational decision. Based on our evidence and theorizing, we cannot take a strong stance on this issue. On the one hand, novices are probably, on average, going to have more similar experiences to a naïve advice-taker, and thus assuming this similarity and relying on novices for advice from direct experience might be useful. However, there could be other cases where novices are not in fact similar (e.g., mostly meat-eaters rating a vegetarian restaurant where the potential diner is vegetarian), so relying on novices' advice might be unhelpful. Similarly, while some experts might be good at synthesizing and extrapolating from data, in other cases, they might be bad at doing so, or do so in a way that is intentionally misguided. Taken together, whether advice-takers are making a mistake is difficult to definitively declare, but could be an interesting route for future research.

Further, while many decisions are made individually, some are made by groups, such as hiring decisions made by departments. Determining whether our results extrapolate to such settings could be interesting for future research. One key moderator could be the composition of the group in terms of expertise: if the group sees themselves as mostly novices, then the patterns we find in this manuscript might emerge as well. But if the group is a mix of novices and experts, people's reliance on novices in particular could change (as novices are seen as having less similar experiences to some members in the group). Given many impactful organizational decisions (e.g., hiring, promotion, etc.) are made by groups, future research could benefit from addressing this.

Lastly, our studies do not test the dynamics of advice taking and learning over time. For example, someone could seek advice from a novice and expert about a job choice, decide to follow the advice of one entity, and detest the job they accepted. Such experience with the outcome of the advisor's judgment might change how likely people are to seek advice from data or direct experience in the future. Future research could explore these dynamics.

Author Note

We would like to thank the University of Alberta Social Sciences and Humanities Research Council General Research Fund for supporting this work. We would also like to thank Joe Simmons, Quentin Andre, and Nick Reinholtz for their feedback on this work. Corresponding author: Katie S. Mehr.

CRediT authorship contribution statement

Katie S. Mehr: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Matt Meister:** Writing – review & editing, Visualization, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.obhdp.2026.104476.

References

Aalbers, R., & Smit, A. (2025). Advice tie reallocation under organizational downsizing: A longitudinal network study. *European Management Journal*. https://doi.org/10.1016/j.emj.2025.01.009

Ache, F., Rader, C., & Hütter, M. (2020). Advisors want their advice to be used – but not too much: An interpersonal perspective on advice taking. *Journal of Experimental Social Psychology, 89*. https://doi.org/10.1016/j.jesp.2020.103979

André, Q., & Reinholtz, N. (2024). Pre-Registered Interim Analysis Designs (PRIADs): Increasing the Cost-Effectiveness of Hypothesis Testing. *Journal of Consumer Research*. https://doi.org/10.1093/jcr/ucae028

Barneron, M., & Yaniv, I. (2020). Advice-giving under conflict of interest: Context enhances self-serving behavior. *Journal of Experimental Social Psychology, 91*. https://doi.org/10.1016/j.jesp.2020.104046

Bickman, L. (1974). The Social Power of a Uniform. *Journal of Applied Social Psychology, 4*(1), 47–61. https://doi.org/10.1111/j.1559-1816.1974.tb02599.x

Blunden, H., Logg, J. M., Brooks, A. W., John, L. K., & Gino, F. (2019). Seeker beware: The interpersonal costs of ignoring advice. *Organizational Behavior and Human Decision Processes, 150*, 83–100. https://doi.org/10.1016/j.obhdp.2018.12.002

Bonaccio, S., & Dalal, R. S. (2006). Advice taking and decision-making: An integrative literature review, and implications for the organizational sciences. *Organizational Behavior and Human Decision Processes, 101*(2), 127–151. https://doi.org/10.1016/j.obhdp.2006.07.001

Bushman, B. J. (1988). The Effects of Apparel on Compliance: A Field Experiment with a Female Authority Figure. *Personality and Social Psychology Bulletin, 14*(3), 459–467. https://doi.org/10.1177/0146167288143004

Cialdini, R. B., Kallgren, C. A., & Reno, R. R. (1991). *A focus theory of normative conduct: A theoretical refinement and reevaluation of the role of norms in human behavior. In Advances in experimental social psychology* (Vol. 24,, 201–234.

Cialdini, R. B., & Trost, M. R. (1998). Social influence: Social norms, conformity, and compliance. In D. T. Gilbert, & S. T. Fiske (Eds.), *The handbook of social psychology* (pp. 151–192). McGraw-Hill.

Collins, E. C., Percy, E. J., Smith, E. R., & Kruschke, J. K. (2011). Integrating advice and experience: Learning and decision making with social and nonsocial cues. *Journal of Personality and Social Psychology, 100*(6), 967–982. https://doi.org/10.1037/a0022982

Daley, B. J. (1999). Novice to Expert: An Exploration of How Professionals Learn. *Adult Education Quarterly, 49*(4), 133–147. https://doi.org/10.1177/074171369904900401

Danziger, S., Montal, R., & Barkan, R. (2012). Idealistic advice and pragmatic choice: A psychological distance account. *Journal of Personality and Social Psychology, 102*(6), 1105–1117. https://doi.org/10.1037/a0027013

Deutsch, M., & Gerard, H. B. (1955). A study of normative and informational social influences upon individual judgment. *The Journal of Abnormal and Social Psychology, 51*(3), 629–636. https://doi.org/10.1037/h0046408

Essig, R. A. (2024). The preference for users to experts in the domain of online product ratings. *Journal of Business Research, 173*. https://doi.org/10.1016/j.jbusres.2023.114455

Evers, E. R. K., Inbar, Y., & Zeelenberg, M. (2014). Set-fit effects in choice. *Journal of Experimental Psychology. General, 143*(2), 504–509. https://doi.org/10.1037/a0033343

Fadel, K., Jensen, M., Matthews, M., & Meservy, T. (2022). *An Empirical Examination of Peer vs. Expert Advice in Online Forums*.

Feng, B., & MacGeorge, E. L. (2006). Predicting receptiveness to advice: Characteristics of the problem, the advice-giver, and the recipient. *Southern Communication Journal, 71*(1), 67–85.

Fox, S. (2013). After Dr Google: Peer-to-Peer Health Care. *Pediatrics, 131*(Supplement_4), S224–S225. https://doi.org/10.1542/peds.2012-3786K

Giffin, K. (1967). The contribution of studies of source credibility to a theory of interpersonal trust in the communication process. *Psychological Bulletin, 68*(2), 104.

Goldsmith, D. J. (1999). Content-based resources for giving face sensitive advice in troubles talk episodes. *Research on Language and Social Interaction, 32*(4), 303–336.

Goldstein, N. J., Cialdini, R. B., & Griskevicius, V. (2008). A Room with a Viewpoint: Using Social Norms to Motivate Environmental Conservation in Hotels. *Journal of Consumer Research, 35*(3), 472–482.

GPT-5 system card. (2025). OpenAI. https://cdn.openai.com/gpt-5-system-card.pdf?utm_source=chatgpt.com.

Harvey, N., & Fischer, I. (1997). Taking Advice: Accepting Help, Improving Judgment, and Sharing Responsibility. *Organizational Behavior and Human Decision Processes, 70*(2), 117–133. https://doi.org/10.1006/obhd.1997.2697

Hilmert, C. J., Kulik, J. A., & Christenfeld, N. J. S. (2006). Positive and negative opinion modeling: The influence of another's similarity and dissimilarity. *Journal of Personality and Social Psychology, 90*(3), 440–452. https://doi.org/10.1037/0022-3514.90.3.44

Hoffman, R. R., Shadbolt, N. R., Burton, A. M., & Klein, G. (1995). Eliciting Knowledge from Experts: A Methodological Analysis. *Organizational Behavior and Human Decision Processes, 62*(2), 129–158. https://doi.org/10.1006/obhd.1995.1039

Hofmann, D. A., Lei, Z., & Grant, A. M. (2009). Seeking help in the shadow of doubt: The sensemaking processes underlying how nurses decide whom to ask for advice. *Journal of Applied Psychology, 94*(5), 1261–1274. https://doi.org/10.1037/a0016557

Hovland, C. I., Janis, I. L., & Kelley, H. H. (1953). *Communication and persuasion*.

Hsee, C. K. (1996). Elastic justification: How unjustifiable factors influence judgments. *Organizational Behavior and Human Decision Processes, 66*(1), 122–129.

Hütter, M., & Fiedler, K. (2019). Advice taking under uncertainty: The impact of genuine advice versus arbitrary anchors on judgment. *Journal of Experimental Social Psychology, 85*. https://doi.org/10.1016/j.jesp.2019.103829

Jungermann, H., & Fischer, K. (2004). *Using Expertise and Experience for Giving and Taking Advice*. In The Routines of Decision Making: Psychology Press.

Kelman, H. C. (1958). Compliance, identification, and internalization three processes of attitude change. *Journal of Conflict Resolution, 2*(1), 51–60. https://doi.org/10.1177/002200275800200106

Krishnamurti, T. N., Kumar, V., Simon, A., Bhardwaj, A., Ghosh, T., & Ross, R. (2016). A review of multimodel superensemble forecasting for weather, seasonal climate, and hurricanes. *Reviews of Geophysics, 54*(2), 336–377. https://doi.org/10.1002/2015RG000513

Kupor, D., Brucks, M. S., & Huang, S.-C. (2019). And the winner is ? Forecasting the outcome of others' competitive efforts. *Journal of Personality and Social Psychology, 117*(3), 500–521. https://doi.org/10.1037/pspa0000165

Lee, F. (1997). When the Going Gets Tough, Do the Tough Ask for Help? Help Seeking and Power Motivation in Organizations. *Organizational Behavior and Human Decision Processes, 72*(3), 336–363. https://doi.org/10.1006/obhd.1997.2746

McDonald, R. I., & Crandall, C. S. (2015). Social norms and social influence. *Current Opinion in Behavioral Sciences, 3*, 147–151. https://doi.org/10.1016/j.cobeha.2015.04.006

Meshi, D., Biele, G., Korn, C. W., & Heekeren, H. R. (2012). How Expert Advice Influences Decision Making. *PLoS ONE, 7*(11). https://doi.org/10.1371/journal.pone.0049748

Miller, D. T., & Prentice, D. A. (1996). *The construction of social norms and standards*.

Milyavsky, M., & Gvili, Y. (2024). Advice taking vs. combining opinions: Framing social information as advice increases source's perceived helping intentions, trust, and influence. *Organizational Behavior and Human Decision Processes, 183*, Article 104328. https://doi.org/10.1016/j.obhdp.2024.104328

Parks, C. D., Sanna, L. J., & Berel, S. R. (2001). Actions of Similar Others as Inducements to Cooperate in Social Dilemmas. *Personality and Social Psychology Bulletin, 27*(3), 345–354. https://doi.org/10.1177/0146167201273008

Patt, A. G., Bowles, H. R., & Cash, D. W. (2006). Mechanisms for enhancing the credibility of an adviser: Prepayment and aligned incentives. *Journal of Behavioral Decision Making, 19*(4), 347–359. https://doi.org/10.1002/bdm.532

Phillips, J. M. (1999). Antecedents of Leader Utilization of Staff Input in Decision-Making Teams. *Organizational Behavior and Human Decision Processes, 77*(3), 215–242. https://doi.org/10.1006/obhd.1998.2819

Pornpitakpan, C. (2004). The Persuasiveness of Source Credibility: A Critical Review of Five Decades' Evidence. *Journal of Applied Social Psychology, 34*(2), 243–281. https://doi.org/10.1111/j.1559-1816.2004.tb02547.x

Price, P. C., & Stone, E. R. (2004). Intuitive evaluation of likelihood judgment producers: Evidence for a confidence heuristic. *Journal of Behavioral Decision Making, 17*(1), 39–57. https://doi.org/10.1002/bdm.460

Rapach, D., & Zhou, G. (2013). Chapter 6—Forecasting Stock Returns. In G. Elliott & A. Timmermann (Eds.), *Handbook of Economic Forecasting* (Vol. 2, pp. 328–383). Elsevier. DOI: 10.1016/B978-0-444-53683-9.00006-2.

Rimal, R. N., Lapinski, M. K., Cook, R. J., & Real, K. (2005). Moving Toward a Theory of Normative Influences: How Perceived Benefits and Similarity Moderate the Impact of Descriptive Norms on Behaviors. *Journal of Health Communication, 10*(5), 433–450. https://doi.org/10.1080/10810730591009880

Rota, L. M., & Zellner, D. A. (2007). The categorization effect in hedonic contrast: Experts differ from novices. *Psychonomic Bulletin & Review, 14*(1), 179–183. https://doi.org/10.3758/BF03194047

Sah, S., Loewenstein, G., & Cain, D. M. (2013). The burden of disclosure: Increased compliance with distrusted advice. *Journal of Personality and Social Psychology, 104*(2), 289–304. https://doi.org/10.1037/a0030527

Schrah, G. E., Dalal, R. S., & Sniezek, J. A. (2006). No decision-maker is an Island: Integrating expert advice with information acquisition. *Journal of Behavioral Decision Making, 19*(1), 43–60. https://doi.org/10.1002/bdm.514

Schultz, P. W. (1999). Changing behavior with normative feedback interventions: A field experiment on curbside recycling. *Basic and Applied Social Psychology, 21*(1), 25–36.

See, K. E., Morrison, E. W., Rothman, N. B., & Soll, J. B. (2011). The detrimental effects of power on confidence, advice taking, and accuracy. *Organizational Behavior and Human Decision Processes, 116*(2), 272–285.

Stephens, R. G., Dunn, J. C., Rao, L.-L., & Li, S. (2015). Exploring the knowledge behind predictions in everyday cognition: An iterated learning study. *Memory & Cognition, 43*(7), 1007–1020.

Van Swol, L. M., & Ludutsky, C. L. (2007). Tell me something I don't know: Decision makers' preference for advisors with unshared information. *Communication Research, 34*(3), 297–312.

Wood, W. (2000). Attitude Change: Persuasion and Social Influence. *Annual Review of Psychology, 51*(Volume 51, 2000), 539–570. DOI: 10.1146/annurev.psych.51.1.539.

Yaniv, I. (2004). Receiving other people's advice: Influence and benefit. *Organizational Behavior and Human Decision Processes, 93*(1), 1–13. https://doi.org/10.1016/j.obhdp.2003.08.002

Yaniv, I., & Choshen-Hillel, S. (2012). When guessing what another person would say is better than giving your own opinion: Using perspective-taking to improve advice-taking. *Journal of Experimental Social Psychology, 48*(5), 1022–1028. https://doi.org/10.1016/j.jesp.2012.03.016

Yaniv, I., Choshen-Hillel, S., & Milyavsky, M. (2011). Receiving advice on matters of taste: Similarity, majority influence, and taste discrimination. *Organizational Behavior and Human Decision Processes, 115*(1), 111–120. https://doi.org/10.1016/j.obhdp.2010.11.006

Yaniv, I., & Kleinberger, E. (2000). Advice Taking in Decision Making: Egocentric Discounting and Reputation Formation. *Organizational Behavior and Human Decision Processes, 83*(2), 260–281. https://doi.org/10.1006/obhd.2000.2909

Zhang, T., Harrington, K. B., & Sherf, E. N. (2022). The errors of experts: When expertise hinders effective provision and seeking of advice and feedback. *Current Opinion in Psychology, 43*, 91–95. https://doi.org/10.1016/j.copsyc.2021.06.011

Zhu, X., Seaver, W., Sawhney, R., Ji, S., Holt, B., Sanil, G. B., & Upreti, G. (2017). Employee turnover forecasting for human resource management based on time series analysis. *Journal of Applied Statistics, 44*(8), 1421–1440. https://doi.org/10.1080/02664763.2016.1214242