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Learning from Stories, Statistics, and Narratives

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Abstract

This article reviews how different types of information shape belief formation. We organize the discussion around two distinctions: whether information supplies evidence or a framework for interpreting evidence, and whether it is qualitative or quantitative. Stories describe individual instances in qualitative terms, whereas statistics summarize many observations numerically. Narratives and quantitative models provide qualitative and quantitative frameworks, respectively, for interpreting evidence. We examine how learning from evidence and learning from models interact: models shape responses to existing and subsequent evidence, while evidence can prompt model revision. We argue that qualitative information engages associative cognitive processes, such as mental simulation and memory retrieval, which tend to give it a larger and more lasting influence on beliefs than quantitative information. We then discuss implications for strategic communication and the supply of information in media markets, and identify challenges and open questions for future research.

Keywords: stories, statistics, narratives, beliefs, learning, qualitative information, models.

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1 INTRODUCTION

"The human mind is a story processor, not a logic processor."
—Jonathan Haidt, *The Righteous Mind* (2012)

People often learn about the world through stories and narratives. A story is an anecdote about some event: a friend's restaurant closed after a rent increase, a coworker made substantial gains on tech stocks, or an aunt developed debilitating symptoms after starting a new medication. A narrative connects events to underlying causes, for example, that rising rents force restaurants out of business. Such narratives can shape beliefs even without new data by altering how people interpret existing evidence. Stories and narratives share certain features and can give rise to systematic misperceptions about the world, especially when the stories people encounter are highly selected or narratives oversimplify the underlying causal relationships.

This article reviews how different types of information shape belief formation. We organize the discussion around two distinctions. First, whether information supplies new evidence or a framework for interpreting evidence. Second, whether the information is qualitative or quantitative in nature. Table 1 uses these distinctions to define four different types of information: stories, statistics, narratives, and quantitative models. These categories describe components of communication that sometimes appear together in real-world information environments.

Table 1: Evidence and Interpretation: A Taxonomy of Information

	Qualitative	**Quantitative**
Evidence	**Stories** describe particular cases in qualitative terms. *"After a tax increase, Maria closed the bakery she had run for years, laid off her longtime staff, and said goodbye to regulars who gathered there each morning."*	**Statistics** summarize observations across cases. *"Eight percent of small businesses closed last year."*
Interpretation	**Narratives** specify perceived causal relationships without quantifying their strength. *"Higher taxes increase business closures."*	**Quantitative models** specify relationships and their magnitudes. *"A one-percentage-point tax increase raises the business closure rate by half a percentage point."*

We use *stories* to refer to qualitative content about individual instances, and *statistics* to refer to numerical summaries of observations. In practice, the two often appear together: stories can include numerical details and draw on statistics to place individual cases in context. We use *narratives* to refer to qualitative causal models through which evidence is interpreted, whether to explain a particular instance or a broader class of events. Quantitative models, which are mostly

used in professional settings, additionally specify numerical relationships through parameters, equations, or conditional distributions. Either type of model can guide the interpretation of stories and statistics.

Section 2 formalizes these distinctions in a setting where a recipient learns about a feature of the data-generating process. Messages can supply evidence or propose changes to the model through which evidence is interpreted. The distinction between qualitative and quantitative information turns on whether it states magnitudes for population features or relationships. Stories leave recipients to assess what generalizes from a particular case; narratives leave them to quantify the relationships asserted.

Building on this framework, Section 3 examines learning from evidence and learning from models, and how the two interact. Models can change beliefs without supplying new observations by reinterpreting existing evidence, and can shape responses to subsequent information. Evidence can, in turn, prompt model revision (Ambuehl et al., 2026; Schwartzstein & Sunderam, 2021).

We next move to our second distinction, which concerns learning from qualitative versus quantitative information. Section 4 outlines a cognitive account of why qualitative information tends to influence beliefs more than quantitative information. People more readily connect qualitative information to familiar experiences (Collins & Loftus, 1975; Evans & Stanovich, 2013; Kahneman, 2011), yet often struggle to process quantitative information (Augenblick et al., 2025; Enke et al., 2026). Qualitative information is often perceived to be more informative since it facilitates mental simulation and recall (Barsalou, 1999; Bordalo et al., 2025a; Tulving, 1972).

What are the implications of the findings covered in this review for the supply side of information? Section 5 examines how senders may strategically choose both the evidence they present and the model through which it is interpreted. Stories allow senders to select concrete cases, whereas narratives draw attention towards a selected set of explanatory variables. We review evidence that communicators' strategic incentives affect the prevalence and nature of stories and narratives in public discourse and media markets.

Finally, Section 6 discusses three methodological obstacles when studying the belief impact of qualitative information: its high dimensionality, its context dependence, and the difficulty of defining rational benchmarks for belief updating. It also discusses how researchers can leverage large language models to measure and craft qualitative information treatments in ways that allow for a more systematic assessment of underlying psychological mechanisms. Section 7 concludes.

The review is intended to speak to economists who model learning, to behavioral and experimental researchers who study how people process different forms of information, and to policymakers who design information interventions. Our review complements recent surveys on salience and attention (Bordalo et al., 2022; Loewenstein & Wojtowicz, 2025), information processing (Benjamin, 2019), mental models (Ambuehl et al., 2026), narratives (Roos & Reccius, 2024), cognitive economics (Enke, 2026; Oprea & Woodford, 2026), and motivated memory

(Amelio & Zimmermann, 2023). We differ from these reviews by focusing specifically on differences in learning from stories, statistics, and narratives and on the underlying psychological mechanisms.

2 FRAMEWORK

We distinguish information along two dimensions: whether it supplies evidence or an interpretation of evidence, and whether it is qualitative or quantitative. Stories and statistics convey evidence about particular cases and collections of observations, respectively. Narratives and quantitative models specify relationships through which evidence is interpreted. These categories describe distinct components of communication: a single message can combine a story, a statistic, and a causal explanation. This section introduces a simple environment to make these distinctions precise.

2.1 Setup

A recipient wants to learn a feature θ of the state of the world ω. The state describes the data-generating process: units i, such as households or firms, are draws from ω. Each unit is described by a vector of K attributes, $x_i = (x_i^1, \ldots, x_i^K)$, such as a business's sector, tax exposure, rent change, and closure status. The feature of interest is a function of the state, $\theta = g(\omega)$. It can be a feature of the joint distribution of attributes, such as the share of businesses that close or the probability that a business with given attributes closes, or a causal effect, such as how a tax increase changes the closure rate.*

The recipient receives a message m. A message consists of two components, either of which can be empty: *evidence* reports attributes of some units, and an *interpretation* proposes how variables relate.

How does the recipient learn about θ from such a message? Updating beliefs requires a hypothesis about how θ relates to the reported attributes and about how the reported units were selected. We call this hypothesis the recipient's model M. The model determines (i) which attributes are relevant, i.e., connected to θ; (ii) in which direction and by how much relevant evidence moves beliefs about θ; and (iii) how representative the reported units are taken to be. M can be a fully explicit, formal model, a purely qualitative account, or entirely implicit. We do not require that the recipient can report, or is even aware of, their model. Given a prior about θ, the recipient forms beliefs as

$$\text{posterior} = B(\text{prior}, m, M).$$

*The last case is conceptually different from the first two. Different causal structures can generate the same joint distribution but imply different causal effects.

A message m can then change the recipient's beliefs in two ways. First, its evidence is processed through the current model M. Second, its interpretation can propose a change to M, which affects how previously received and future evidence is incorporated into beliefs. The two routes interact: M determines which evidence is relevant and how much weight it receives, while evidence that fits poorly under M can prompt a revision of it.

Characterizing the message components The two message components differ along two margins, which generate the taxonomy of Table 1. The first distinction concerns whether a message provides evidence or proposes an interpretation of that evidence. Evidence describes units drawn from ω. Whether it is informative about θ and how much depends on the recipient's prior information and model. A report moves beliefs only if its likelihood varies with θ given M. In particular, a report can be redundant or non-diagnostic. Interpretation makes a claim about how the variables in ω are related. It moves beliefs by changing M, which happens either because the recipient credits its source with knowledge about ω or because it organizes evidence the recipient already holds.

The second distinction is about magnitudes. In our terminology, a message is quantitative if it states a number for the feature the recipient wants to learn about. That feature can be a population characteristic or the strength of a relationship between variables. A statistic qualifies because it summarizes several units in the same form as the population quantity it relates to. It is computed from a sample, but it is offered as a value for the target θ. A story does not qualify, even when it includes numbers, because those numbers describe one unit and not the population. The same logic applies to interpretations. A narrative says that two variables are linked and in which direction, while a quantitative model goes further and adds by how much. In short, quantitative information tells the recipient how often something happens in the population, or how strongly two variables move together. Qualitative information describes what happened in a case or which way an influence runs, leaving the magnitude open.

2.2 Evidence: Statistics and Stories

Evidence is a report of attributes of units. It specifies which units I it includes, which attributes $c \subseteq \{1, \ldots, K\}$ it covers, and the realizations x_i^j for $i \in I$ and $j \in c$. A statistic summarizes several units, $|I| > 1$, through a summary function, $t = T((x_i)_{i \in I})$, such as the share of the reported businesses that closed. A story, by contrast, directly reports the covered attributes of a single unit, $|I| = 1$. Hearing that Maria's bakery closed after a tax increase is a story about one business. Hearing that eight percent of small businesses closed last year is a statistic over many.

Aggregation over multiple units is the definitional difference between a statistic and a story. We stipulate this distinction because it aligns with the second distinction drawn above. Specifically, a statistic summarizes units in the same form as the population feature and therefore

typically states a magnitude for it, unlike a story. We view other differences between statistics and stories as typical rather than definitional and describe them at the end of this section.

A story is nonetheless more than a statistic computed over a single unit, because aggregation typically reduces the dimensionality of information. Typically, the summary function focuses on a single attribute and aggregates its realizations across many units into a one-dimensional statistic t, such as a share or an average. An attribute can enter that summary only if it is recorded in the same form for every unit. A story applies no summary and passes on the realizations of its unit as they are. Its coverage c can therefore include contextual attributes, which describe the particular circumstances of a unit: the order in which things happened, what the people involved believed caused them, and how they saw them. The story about Maria's bakery can report that she ran it for twenty years, that her rent rose in the same year, and that she blamed the tax for her decision to close. A statistic can convey such attributes only after coding them into a common form and aggregating them, as in the share of owners who name taxes as a reason for closing. That step discards most of their content.

2.3 Interpretation: Narratives and Quantitative Models

An interpretation is a claim about the data-generating process ω rather than a description of data generated by it. It corresponds to a subjective representation of which variables matter and how they are causally related (Ambuehl et al., 2026; Andre et al., 2022; Sloman, 2005). A narrative specifies which variables matter for θ, which of them are connected, and what the direction of each connection is. "Higher taxes increase business closures" is a narrative. A quantitative model in addition provides magnitudes, expressed through parameters, equations, or conditional distributions. "A one-percentage-point tax increase raises the business closure rate by half a percentage point" is a quantitative model.

In economics, narratives have been represented as directed acyclic graphs in which each edge stands for a perceived causal link (Eliaz & Spiegler, 2020; Spiegler, 2016, 2020). The graph specifies which variables directly affect which others, but does not by itself specify the signs or magnitudes of these effects. A narrative may additionally assert that a relationship is positive or negative. A quantitative model supplies further structure, such as conditional distributions describing how each variable depends on its direct causes.

In this setup, nothing guarantees that an interpretation is correct. A narrative can omit relevant variables or get a direction wrong. A quantitative model can state miscalibrated magnitudes for existing relationships or specify one where none exists.

An interpretation communicated in a message is the same kind of object as the recipient's model M. Receiving one may lead the recipient to replace or extend M (Eliaz & Spiegler, 2020; Schwartzstein & Sunderam, 2021). Whether this happens, and what makes a proposed interpretation persuasive, are questions we turn to in Section 3.

2.4 Message Composition

A given message often combines different types of components. "Maria's bakery closed after a tax increase" is a story in our sense, reporting two attributes of one unit and their order. "Maria's bakery closed because of the tax increase" adds a causal claim. A causal attribution is not observable in a draw but claims something about how variables relate. The second sentence is therefore a message that combines a story with a narrative. A similar decomposition applies to quantitative information. "Businesses with high tax exposure closed at twice the rate of other businesses" is a statistic, because it summarizes an attribute of a set of observed units. "A tax increase doubles the closure rate", by contrast, is a quantitative model. It makes a claim about what a change in taxes would do. A message that reports the first and then asserts the second combines a statistic with a quantitative model, akin to the Maria example that combines a story with a narrative. Reading a sequence of events covered in a story or a co-occurrence of attributes across cases in a statistic as a causal effect is itself an act of interpretation. Finally, note that a message can also mix the rows and columns of Table 1 in other ways, for example when the story of Maria's closure is reported alongside the quantitative model about the aggregate closure rate.

2.5 Belief Formation with Qualitative Information

A key difference between qualitative and quantitative information lies in whether they provide magnitudes. Because qualitative evidence and qualitative interpretations lack magnitudes, the recipient must fill this gap when forming beliefs. To see this for the story–statistic comparison, consider a recipient who wants to estimate a population share. A statistic states a candidate value for that share. The recipient still relies on M to decide how much weight the reported value deserves, given how the units were selected and how many there are, but not to supply the magnitude itself. By contrast, a story with $|I| = 1$ states no magnitude for any population feature, so the recipient must construct one from M. Similarly, for the narrative–model comparison, a narrative leaves open how strong the stated relationships are, and the recipient's current model M has to supply that strength. Hence, both for evidence and interpretation, M fills back in what qualitative content leaves out.

Under a Bayesian benchmark, the missing magnitudes would come out of calculations that combine prior and model. Such calculations are demanding and unlikely to be carried out in practice. Instead, the recipient may retrieve the missing magnitudes from memory, by pulling up similar cases (Bordalo et al., 2025a), imagining the outcome (Schacter et al., 2012), and noticing how easily something comes to mind (Tversky & Kahneman, 1973). Relying on what is accessible in memory when incorporating qualitative information can create systematic distortions, which we review in Section 4. That recipients have to "fill in the gap" and supply the magnitude is precisely the way in which qualitative information "engages" the recipient. It makes the recipient's memory and imagination part of the belief formation process.

2.6 Other Typical Differences

We treat evidence versus interpretation and qualitative versus quantitative information as the definitional distinctions of this review. Statistics and stories differ along at least two further dimensions that are typical but not definitional.

Selection In both cases the reported units are selected somehow. A statistic may be based on a random sample, but random sampling is not part of the definition of a statistic. Similarly, a story's case need not be representative of the population of cases. The recipient's model M includes an assumption about this selection, and Section 5 examines communicators' strategic incentives.

Presentation A report can be verbal or numerical, sparse or vivid. Stories are typically told in words with contextual detail, statistics stated as numbers. Comparisons between stories and statistics can therefore vary several dimensions simultaneously: individual versus aggregate evidence, numerical versus verbal presentation, contextual detail, and informational content. A difference in belief responses does not by itself identify which dimension drives the effect. We accordingly distinguish comparisons of these information bundles from interventions that isolate particular features, such as retrieval cues or the presence of a causal explanation.

2.7 Benchmark and Departures

Fixing M, a Bayesian recipient's belief update depends on the content of evidence alone, meaning its units, attributes and realizations. A proposed interpretation moves beliefs only insofar as it changes how past and future evidence is read. The recipient may believe its source knows something about ω or the new interpretation may fit the evidence already received better than M does. These benchmarks organize the departures examined in the remainder of the review.

3 EMPIRICAL EVIDENCE ON LEARNING FROM DATA AND LEARNING FROM MODELS

People learn both from evidence—such as stories and statistics—and from models—such as narratives and quantitative models. These processes are interdependent: models shape how people interpret evidence, while evidence can influence which models they adopt. A single message may supply both evidence and a framework for interpreting it. This section reviews empirical research on learning from evidence and learning from models, examining how each shapes beliefs and how the two interact.

3.1 Learning from evidence

Learning from evidence has long been a central concern in economics and psychology. Laboratory experiments typically use stylized quantitative signals and known data-generating processes to identify departures from Bayesian updating (Benjamin, 2019). A complementary literature uses naturalistic information, often embedded in surveys, to study how evidence about economic and social outcomes affects beliefs and policy views (Alesina et al., 2023; Haaland et al., 2023). Together, these literatures examine both how people weight evidence and how its presentation shapes its influence.

Behavioral attenuation A recurring finding is insufficient sensitivity to the statistical properties of evidence, including prior probabilities, sample size, and signal strength (Benjamin, 2019). Recent work attributes these patterns to information processing constraints. Enke & Graeber (2023) show that greater cognitive uncertainty about the appropriate judgment is associated with stronger compression of reported probabilities toward intermediate values. Across a broader range of tasks, Enke et al. (2026) document behavioral attenuation: greater cognitive uncertainty and task complexity are associated with less elastic responses to quantitative fundamentals. This does not imply uniform underreaction: weak signals can generate overinference, whereas strong signals can generate underinference (Augenblick et al., 2025).

Representativeness and diagnostic expectations A second influential approach traces distortions in learning from evidence to what comes to mind when people evaluate hypotheses (Gennaioli & Shleifer, 2010). Its starting point is the representativeness heuristic: people judge a hypothesis as likely when the evidence resembles it (Kahneman & Tversky, 1972; Tversky & Kahneman, 1974). Gennaioli & Shleifer (2010) formalize this idea as local thinking. Decision makers consider only the scenarios that come to mind first, which are those most representative of the hypothesis, and neglect the rest. Applied to beliefs about groups, representativeness yields stereotypes with a kernel of truth: people exaggerate true differences between groups by overweighting the types that are relatively more frequent in one group than in a comparison group (Bordalo et al., 2016). Applied to news, it yields diagnostic expectations. Forecasters overweight the states whose likelihood rises most in light of new data and therefore overreact (Bordalo et al., 2019, 2018). In survey data, individual macroeconomic forecasts overreact to news even though consensus forecasts underreact (Bordalo et al., 2020a). Representativeness therefore governs how the recipient's model M maps evidence into beliefs about θ: it inflates the perceived diagnosticity of evidence that points toward a distinctive hypothesis. Bordalo et al. (2023a) bring this logic to the classic problems used to document departures from Bayesian updating. They show that answers to standard statistical problems are often multimodal and shift with changes in wording that leave the substance of the problem unchanged. They account for these patterns with a model in which people represent each hypothesis by its most salient

features and use only the statistics tied to those features.

Memory Memory provides a further link between evidence and beliefs. In memory-based models, people evaluate a hypothesis by retrieving instances of it. Retrieval favors instances that are similar to the current cue, and other instances interfere with it (Bordalo et al., 2021, 2023b, 2020b). Representativeness then emerges from the structure of recall rather than from a separate heuristic (Bordalo et al., 2021). Enke et al. (2024) provide experimental evidence on associative recall in updating. When news arrives with a memorable context, new information cues the recall of past news that shares that context, and beliefs about fundamentals overreact. In a betting market, the same recall pattern makes prices overreact. Section 4.4 returns to these mechanisms when comparing the persistence of qualitative and quantitative evidence. Jiang et al. (2025) provide field evidence that underscores the importance of associative recall. They show that retail investors form return expectations by selectively recalling past experiences that resemble current conditions. Hence, when the market is rising, investors remember their own past performance more favorably and expect higher future returns.

Experience Personal experience is a distinct source of evidence. An experience reports what happened to a single unit, often the recipient, and in this respect resembles a story that is lived rather than told. A large literature documents that experiences shape beliefs about population quantities well beyond their statistical weight (for a review, see Malmendier, 2021). Individuals who lived through low stock market returns take less financial risk and expect lower returns (Malmendier & Nagel, 2011). Inflation expectations overweight the inflation people experienced during their lifetimes (Malmendier & Nagel, 2016).

Stories If experiences are evidence that people live through, stories convey the experiences of others. A parallel literature examines how people form judgments from such qualitative accounts of individual cases (Borgida & Nisbett, 1977; Freling et al., 2020). Early experiments show that people generalize from vivid examples even when explicitly told that these examples are atypical (Hamill et al., 1980). Other early work highlights the role of stories in organizing memory. Bower & Clark (1969) show that constructing coherent stories around otherwise unrelated words substantially improves subsequent recall, while research on scripts and schemas examines how familiar event structures organize comprehension and memory (Mandler, 1984; Schank & Abelson, 1977). More recent work connects differences in recall to the persistence of beliefs. Graeber et al. (2024) find that the belief impact of stories decays less over time than that of statistics, with selective retrieval accounting for much of the difference.

3.2 Learning from models

Theoretical approaches Models identify relevant variables and specify relationships through which observations generate predictions. In economic theory, narratives have been represented as directed acyclic graphs encoding perceived causal structure (Eliaz & Spiegler, 2020; Spiegler, 2016, 2020). Schwartzstein & Sunderam (2021) study persuasion through models that organize evidence the receiver already possesses. A sender can influence beliefs by proposing an interpretation that fits the observed history and supports the sender's desired prediction (see also Aina, 2025). Beliefs can therefore change without new observations.

The scope for persuasion through models depends on how receivers evaluate competing interpretations, and accuracy may not be their only criterion. In Eliaz & Spiegler (2020), people prefer causal models under which expectations about the future are more optimistic. More generally, learning within a misspecified model need not correct mistaken beliefs, because the observations agents encounter may not reveal the model's errors (Bohren & Hauser, 2021, 2025; Heidhues et al., 2018, 2023). Such errors can persist even when people consider alternative models: Ba (2026) shows that a misspecified model can survive comparison with the true model despite an unlimited stream of observations. Correcting mistaken beliefs may therefore require changing the model through which people interpret evidence, rather than simply providing more data.

Which models do people adopt? Which models people adopt when confronted with competing interpretations is the subject of several experimental and survey studies (Aina & Schneider, 2026; Baader et al., 2026; Barron & Fries, 2024a,b; Esponda et al., 2024; Fan & Fries, 2026; Fréchette et al., 2024; Grass et al., 2026). That causal narratives can affect decisions even when they are incorrect is shown by Kendall & Charles (2022), who document departures from rational benchmarks. As for what makes a narrative appealing, several features play a role. A better fit with the observed historical data increases its persuasive force (Barron & Fries, 2024b). Simplicity matters as well: people favor simpler causal models even where richer alternatives are available (Ambuehl & Thysen, 2024). A further issue concerns how people act when uncertainty over competing models remains. They may simplify this uncertainty when making a decision rather than taking it into account (Musolff & Zimmermann, 2025).

Where do the subjective models through which people interpret the world come from? Personal experience is one natural source. In Malmendier & Nagel (2016), individuals learn the parameters of the inflation process from the inflation they have lived through, so experience shapes the perceived persistence of inflation and not only its expected level. Experience can also shape which variables people attend to. In panel surveys of German households and firms, Link et al. (2026) find that respondents who previously experienced adverse inflation pay more attention to inflation when a new inflation shock hits, consistent with similarity-based recall.

The experience effects reviewed in Section 3.1 may therefore operate through two channels. Experiences supply evidence, and they also shape the interpretations through which people read subsequent evidence. To what extent the documented experience effects reflect learning a model rather than retrieving evidence is largely an open question.

Models shape learning from data Measurement studies reveal substantial heterogeneity in the models people bring to economic questions. Households and experts differ in their perceived responses of macroeconomic outcomes to shocks (Andre et al., 2022). Related differences appear in reasoning about taxation, trade, and climate policy (Dechezleprêtre et al., 2025; Stantcheva, 2021, 2022), in financial market beliefs (Andre et al., 2026b; Bauer et al., 2024), and in zero-sum views of the economy (Chinoy et al., 2026). These findings suggest that disagreement can reflect different perceived relationships between variables, in addition to different observations or prior beliefs about a particular outcome.

Andre et al. (2026a) provide a direct connection between models and updating. They show that narratives causally affect responses to subsequent evidence. Respondents first receive a narrative emphasizing either government spending or the energy crisis and then receive a forecast of government spending. Inflation expectations respond more strongly to the spending forecast among recipients of the government-spending narrative. A model therefore does more than change a current prediction: it changes how later evidence is used. This is the clearest sense in which learning from models and learning from data interact.

Some papers establish a link between narratives and behaviors. Research on long-term unemployment examines how causal narratives relate to job search (Mahlstedt et al., 2026). Evidence from competing television programs during the early COVID-19 pandemic links exposure to different narratives about the pandemic to different preventive behavior and health outcomes (Bursztyn et al., 2022). Such communication can alter both factual beliefs and interpretations, making it difficult to attribute its effects exclusively to either data or models. Narratives can also alter how people interpret others' behavior. For example, narratives can supply moral justifications or excuses (Bénabou et al., 2020), and rationales can provide social cover for expressing stigmatized positions (Bursztyn et al., 2023).

3.3 Information Interventions as a mix of stories, statistics and narratives

Information provision experiments have become a central tool for studying belief formation. Policymakers use them to correct misperceptions. Researchers also use randomized information interventions to generate exogenous variation in beliefs. Applications now span most applied fields, including taxation, inequality and mobility, immigration, and macroeconomic expectations (Alesina et al., 2018; Chetty & Saez, 2013; Coibion & Gorodnichenko, 2015; Roth et al., 2022). Information interventions often combine evidence and interpretation, as well as qualitative and

quantitative content. We review existing evidence with this framework in mind.

Evidence versus interpretation Most information provision experiments supply quantitative evidence, such as statistics on the inflation rate (Coibion et al., 2020), the level of inequality (Kuziemko et al., 2015), and the rate of intergenerational mobility (Alesina et al., 2018), or professional forecasts of a recession (Roth & Wohlfart, 2020).

Two findings emerge from this literature. Effects on beliefs, although sizable on impact, tend to decay quickly, and effects on downstream behavior and policy views are often muted (Haaland et al., 2023). Our framework suggests one reason for the second regularity. Policy views typically depend not only on the level of a variable but also on perceived causal relationships. A statistic that corrects a factual misperception does not necessarily change these perceived causal relationships. This is consistent with above that additional data need not correct beliefs rooted in a misspecified model.

A second class of interventions aims to change how people interpret the world. For example, experimental treatments explain the mechanisms and distributional consequences of taxes (Chetty & Saez, 2013; Stantcheva, 2021), trade (Stantcheva, 2022), immigration (Alesina et al., 2023; Haaland & Roth, 2020), or climate policies (Dechezleprêtre et al., 2025).

Qualitative versus quantitative A growing number of studies compare interventions that supply statistical evidence with interventions that include accounts of particular cases, sometimes combined with causal interpretations. Across several settings, these case-based interventions have larger effects on policy attitudes and behavior. In work on racial inequality and immigration, statistical corrections update factual beliefs but often leave policy preferences unchanged, whereas anecdote-based treatments produce larger shifts in policy support (Alesina et al., 2024, 2023). In climate policy, factual information alone slightly reduces demand for additional policy. Pairing the same information with a short fictional account of citizen agency instead increases political efficacy, donations to advocacy groups, and information-seeking about climate marches (Page et al., 2025). This fictional account illustrates a possible sequence of events rather than supplying evidence about an observed case. Emotionally salient news stories can outweigh accurate statistics (Manzoni et al., 2026), and policymakers in Chile are persuaded more by episodic stories than by statistical information (Cruz, 2026).[2] These findings raise the question of why qualitative information can have greater effects on beliefs and behavior than quantitative information. The next section examines cognitive mechanisms that may account for these differences.

[2]Looking at a broader set of policy outcomes, Rodger et al. (2026) provide evidence that negative stories in particular shape policy attitudes.

4 LEARNING FROM QUALITATIVE VERSUS QUANTITATIVE INFORMATION

This section reviews differences in how people learn from qualitative and quantitative information, with a particular focus on the cognitive mechanisms underlying these differences. The core idea of this section is that qualitative information often connects more readily to familiar experiences and associations, making it easier to process, imagine, and recall, and thereby increasing its influence on beliefs irrespective of its informativeness.

4.1 Associative Architecture as the Organizing Principle

The associative account distinguishes between the informativeness of a message and its capacity to activate existing knowledge. Models of associative memory posit that information affects judgments partly through what it brings to mind (Bordalo et al., 2025a,b; Gennaioli & Shleifer, 2010). Related concepts and experiences are activated through links formed by semantic similarity and repeated co-occurrence (Collins & Loftus, 1975). A message can therefore influence judgments through associations that need not reflect its informativeness about the outcome of interest.

Associations can affect both the weight assigned to information and the direction of belief change. Conlon & Kwon (2026) formalize this distinction in a model in which cues bring similar states of the world to mind. A cue's *resonance* determines its weight relative to competing cues, while its *representativeness* determines which outcomes it favors. Greater resonance alone does not imply a shift toward a particular outcome; the direction depends on the states the cue evokes.

This mechanism helps explain when qualitative information may exert greater influence than quantitative information. Stories describe people, circumstances, and events that may evoke familiar experiences; narratives specify causal relationships that may activate familiar explanations. Statistics typically abstract from such contextual detail. Qualitative information may therefore receive greater weight when these cues connect more strongly to recipients' existing knowledge than the numerical summary does. If the resulting associations favor a particular outcome, they may shift beliefs toward it despite contrary statistical evidence. The details generating these associations need not themselves be informative about the outcome.

Early experiments illustrate how influence can diverge from informativeness. Participants in Nisbett & Borgida (1975) make little use of aggregate information about helping behavior when predicting individual behavior. Hamill et al. (1980) find that a richly described individual case affects attitudes toward welfare recipients even when participants are told that it is atypical. Nisbett & Ross (1980) interpret such findings in terms of the greater ease of imagining concrete cases. These results do not identify an associative mechanism, but they are consistent with

the account: individual cases can exert influence that is insufficiently moderated by aggregate evidence or information about their selection.

The central consideration is thus the relationship between information and recipients' existing knowledge, rather than information format alone. Familiar statistics may evoke strong associations, while unfamiliar stories may not. Associations also connect several mechanisms examined below: they can direct attention, support mental simulation and memory, facilitate processing, and evoke emotion. These processes may increase the influence of information without increasing its informativeness. Table 2 summarizes each mechanism and how it applies to qualitative and quantitative information.

4.2 Attention

The associative processes described above can shape beliefs by directing attention toward some features of the available information at the expense of others. Attention determines which attributes and relationships enter consideration and receive weight in judgment (Bordalo et al., 2012, 2013; Kőszegi & Szeidl, 2013).[3] This mechanism is distinct from the selection of information into a message. In the framework of Section 2, coverage c describes which attributes a report includes; attention concerns which of the available attributes the recipient considers. Even when a message contains both a concrete story and an aggregate statistic, recipients may focus on the case and give little consideration to the statistic.

Attention can be guided both by recipients' goals and existing models (*top-down*) and by features of the message that attract attention without deliberate search (*bottom-up*). The associative account suggests why qualitative information may be particularly effective through bottom-up attention. Concrete details in stories can activate familiar experiences and draw attention toward particular attributes or outcomes, leaving less attention for accompanying numerical evidence. Narratives can similarly make particular causal relationships stand out by connecting them to familiar explanations. Once adopted, a narrative can also guide top-down attention by shaping which variables recipients look for in subsequent evidence. Consistent with an attentional channel, Morag & Loewenstein (2025) find that narratives shift valuations by directing attention toward selected attributes.

The implication is that providing relevant quantitative information may have limited effects when qualitative cues draw attention elsewhere. Statistics and quantitative models make frequencies and relationship strengths available, but recipients must attend to these quantities for them to discipline inference. A story about a business closing after a tax increase, for example, may focus attention on that sequence of events while an accompanying closure rate receives little consideration. This provides one route through which qualitative information can exert disproportionate influence even when relevant quantitative evidence is available.

[3] For reviews, see Loewenstein & Wojtowicz (2025) and Bordalo et al. (2022).

Table 2: Cognitive Mechanisms Underlying Differences in Learning from Qualitative and Quantitative Information

Mechanism	Psychological Principle	Qualitative Information	Quantitative Information
Attention	Salience and interpretive frames shape which attributes and relationships enter consideration (Bordalo et al., 2012; Morag & Loewenstein, 2025).	Stories highlight selected attributes of particular cases; narratives emphasize particular variables and causal relationships. Neither necessarily directs attention toward what matters most for inference.	Statistics highlight selected numerical features; quantitative models specify relationship strengths. Recipients may still neglect base rates, correlations, or other relevant inputs.
Imagery and Mental Simulation	People imagine outcomes by retrieving related experiences; similarity shapes which experiences come to mind (Barsalou, 1999; Bordalo et al., 2025a; Schacter et al., 2012).	Concrete cases provide readily imagined instances and connect possible outcomes to familiar experiences.	Abstract summaries may require translation into concrete scenarios; contextual cues can support simulation without adding evidence.
Memory	Encoding, rehearsal, and cue-dependent retrieval shape what remains accessible; competing associations can interfere with recall (Conlon, 2026; Graeber et al., 2024; Schacter, 2008).	People, contexts, and events provide retrieval cues that can sustain belief effects, but persistence depends on subsequent cues and interference from competing associations.	Limited contextual detail can make numerical information harder to retrieve; effective contextual cues can improve recall and sustain its influence on beliefs.
Processing Costs	Representational costs arise from organizing an inference problem; computational costs arise from evaluating and combining its inputs (Ba et al., 2025).	Familiar cases can simplify interpretation; narratives supply variables and causal relationships. Both can suggest a direction of updating without specifying its magnitude.	Interpreting magnitudes and weighting evidence can be demanding; knowing the direction of updating need not imply correctly calibrating its size (Augenblick et al., 2025).
Processing Fluency	The subjective ease of processing information can increase its perceived credibility (Reber et al., 2004).	Descriptions of familiar events and causal relationships can feel easy to understand and therefore seem more credible.	Unfamiliar quantities may feel less immediately understandable; familiar statistics and simple quantitative models can nevertheless be fluent to process.
Emotion	Emotional engagement can strengthen attention and memory for salient details (Kensinger, 2009).	Identifiable people and concrete events can evoke emotional responses, including sympathy, potentially contributing to persistent belief effects.	Abstract aggregates often leave individual experiences less concrete, providing fewer immediate cues for emotional engagement.

Notes: Qualitative information includes stories and narratives; quantitative information includes statistics and quantitative models. The table summarizes the mechanisms discussed in Section 4, organized around how readily information connects to existing knowledge and associations. Much of the direct comparative evidence concerns stories and statistics. The tendencies depend on familiarity, expertise, presentation, and task: contextualization, visualization, and effective retrieval cues can facilitate the use of quantitative information, while unfamiliar stories and complex narratives can be difficult to process. When stories and statistics are combined, contextual cues can support statistical recall, but vivid cases can also lead recipients to rely on individual examples at the expense of aggregate evidence. Greater cognitive accessibility or influence on beliefs does not imply greater accuracy.

4.3 Imagery and Mental Simulation

Beyond directing attention toward particular features of the evidence, qualitative information can also shape beliefs by making particular outcomes easier to imagine. To imagine an outcome they have not directly experienced, people draw on memories of related experiences (Schacter et al., 2012). Bordalo et al. (2025a) model this process as similarity-based recall: memories most similar to the focal event disproportionately shape imagined outcomes and subjective probabilities. Consistent with this mechanism, Bordalo et al. (2026a) find that prompting Dutch households to recall personal financial or health adversities shifts inflation and home-price expectations, with larger shifts when the recalled experience seems more similar to the forecasted outcome.

Stories can facilitate simulation by supplying concrete contextual and emotional detail (Barsalou, 1999). These features contribute to *vividness*: the extent to which information is concrete, emotionally rich, and easy to imagine (Taylor & Thompson, 1982). A story can thus provide a readily imagined instance, whereas an aggregate statistic may require translation into a concrete scenario. In the context of false information, Musolff et al. (2026) find that qualitative information is perceived as more vivid and influences beliefs more strongly than quantitative information, even after authoritative debunking. The role of familiar experience in mental simulation also extends beyond stories about particular cases. Metaphors and analogies may help recipients imagine unfamiliar situations by mapping them onto familiar ones (Andries et al., 2026; Gentner, 1983; Grass, 2026).

4.4 Memory

Beyond shaping what people imagine, qualitative information may also affect what they later remember. Encoding shapes how information is stored, while retrieval determines what comes to mind when a judgment is made (Schacter, 2008). Retrieval can itself strengthen subsequent recall through rehearsal, thereby influencing later beliefs (Conlon, 2026).

Qualitative information can link evidence and explanations to people, contexts, and familiar experiences. These associations may support retention and serve as retrieval cues: later encounters with related people or situations can bring the information back to mind (Craik & Lockhart, 1972; Paivio, 1986; Tulving, 1972). Quantitative information often abstracts from these contextual associations, which may make numerical facts and relationships less accessible when forming subsequent judgments. Economic models formalize related mechanisms by allowing recall to depend on similarity to the current situation, attention at encoding, and representativeness (Bordalo et al., 2023b, 2025b, 2020b; Conlon & Kwon, 2026).

Evidence comparing stories and statistics illustrates how these memory processes can produce differences in belief persistence. Graeber et al. (2024) document that within a day, the belief

impact of a statistic decays by 73%, whereas that of a story decays by 32%. We refer to this difference in persistence as the story–statistic gap. Their experiments identify retrieval as a central mechanism. Changing a retrieval prompt from "The Italian restaurant Napoli," which closely matches a story about Italian cuisine, to "Mr. Jones," which does not, reduces correct recall from 80% to 38%, with corresponding effects on delayed beliefs. Making irrelevant stories more similar to the target prompt likewise reduces recall of the target, from 48% to 31%. The persistence of information thus depends on whether subsequent cues activate the relevant information and whether competing associations interfere with its retrieval.[4]

Graeber et al. (2024) find little difference in belief decay between stories and statistics conditional on correctly recalling the type and direction of the information. The gap arises primarily from whether relevant information is retrieved at all. Up to 80% of observations fall into two classes: information is retrieved and beliefs do not decay, or retrieval fails and beliefs revert fully to the prior. In this setting, differences in learning from stories and statistics therefore reflect selective retrieval more than gradual loss of detail.

We next turn to the recall of narratives and quantitative models. Partial recall may matter for quantitative models in particular: recipients may remember a relationship while forgetting its magnitude. For example, they might retain that higher taxes increase business closures without recalling the size of the proposed effect. A quantitative model could thus persist in memory as a qualitative narrative, continuing to guide the direction of predictions while leaving their magnitude unspecified. Whether qualitative information evokes such memories more strongly than quantitative information remains an open empirical question.

Memory can shape judgments not only through recall of the message itself, but also through the experiences that the message brings to mind. Bordalo et al. (2026b) show that individuals with greater recall fluency respond more strongly to past experiences and current cues, including cues that evoke similar experiences from other domains. This finding suggests a further channel through which qualitative information may influence beliefs: references to familiar people, situations, and causal relationships may facilitate retrieval of experiences beyond those described in the message. Whereas the evidence on stories and statistics highlights whether communicated information remains accessible over time, the recall-fluency findings highlight how current information activates other memories that enter judgment. Whether qualitative information evokes such memories more strongly than quantitative information remains an open empirical question.

[4]Related losses occur in social transmission: when participants relay economic forecasts orally, numerical details frequently fail to come to mind and communication defaults to verbal descriptions (Graeber et al., 2026a).

4.5 Processing Costs

Information that attracts attention may still be difficult to use. Forming a judgment requires recipients to organize the inference problem and evaluate the implications of its inputs. Following Ba et al. (2025), these demands can be distinguished as *representational costs*, associated with constructing a mental representation of the problem, and *computational costs*, associated with drawing inferences within that representation.

Qualitative information can reduce some of these demands by connecting to familiar knowledge. A concrete story can evoke an interpretation grounded in experience, while a narrative can supply variables and causal relationships that recipients would otherwise need to identify themselves. Quantitative information may additionally require interpreting numerical magnitudes and combining inputs with appropriate weights. These operations can be demanding when recipients lack familiarity with the relevant quantities.

The distinction between understanding the direction of information and evaluating its strength illustrates this asymmetry. Augenblick et al. (2025) develop a model in which people know which direction to update but are uncertain about how much to update. Consistent with this account, they document overinference from weak signals and underinference from strong signals. Their findings suggest that extracting a directional implication can be easier than calibrating the magnitude of updating to the signal's diagnosticity. Applied to the comparison here, a qualitative account may convey that an outcome is more likely or that a relationship is positive, while using quantitative evidence requires evaluating how much more likely or how strong the relationship is.

Graeber et al. (2025) provide complementary evidence from earnings announcements on how problem difficulty shifts reliance from quantitative toward simple qualitative information. The authors find that harder-to-value stocks respond more strongly to qualitative information about whether earnings beat or missed expectations, and experiments that manipulate problem difficulty provide supporting causal evidence.

For narratives and quantitative models, however, explicit magnitudes can also reduce processing demands, provided that respondents know how to interpret the magnitudes in the first place. A narrative identifies relevant variables and the direction of their relationships but leaves recipients to supply any magnitudes needed for prediction. A quantitative model provides these magnitudes and can therefore simplify the mapping from inputs to outcomes. For example, "higher taxes increase business closures" leaves the size of the response open, whereas a specified effect per percentage-point tax increase allows recipients to calculate a predicted change in closures. The relative processing advantage thus depends on whether recipients find it harder to use supplied magnitudes or to infer missing ones.

These processing differences depend on familiarity and presentation. Numeracy facilitates the use of quantitative information (Peters et al., 2006), while natural frequencies, icon arrays,

and explicit benchmarks can make numerical relationships easier to interpret (García-Retamero & Galesic, 2010; Gigerenzer & Hoffrage, 1995). Conversely, unfamiliar stories and complex narratives can impose substantial processing demands. The central implication is that qualitative information often supplies an accessible basis for judgment when quantitative evaluation is costly. This accessibility can increase its influence without ensuring that recipients correctly assess the representativeness of a case, the strength of evidence, or the validity of a causal account.

4.6 Processing Fluency

Beyond processing costs, judgments depend on *processing fluency*: the subjective ease of understanding information. Information that feels easier to understand tends to be perceived as more credible (Reber et al., 2004). Qualitative accounts may benefit from this effect because descriptions of events and causal relationships fit familiar ways of understanding the world (Bullock et al., 2021). They may therefore seem more convincing than quantitative information, even when the latter is more informative, particularly when recipients are unfamiliar with the relevant quantities. This advantage depends on familiarity and complexity: a simple statistic or quantitative model may be easier to grasp than an unfamiliar or complex qualitative account.

4.7 Emotion

The preceding discussion emphasizes how qualitative information facilitates understanding and recall. Its influence may also depend on the extent to which it evokes emotional responses (Algan et al., 2025; Manzoni et al., 2026; Mar, 2011), e.g., by identifying individuals who are more relatable (Small et al., 2007). With quantitative evidence, the individual person typically recedes into the background: the recipient learns about frequencies or magnitudes, while the experiences behind these numbers remain less concrete. This difference may also matter for what people retain from the evidence. Emotionally salient details can attract attention and be better remembered (Kensinger, 2009). Emotional engagement may thus contribute to the persistence of qualitative evidence in belief formation. Emotion can also change the significance recipients attach to an outcome, independently of their beliefs about its frequency. A qualitative account of a patient's suffering may therefore increase concern about a condition without improving understanding of its incidence.

4.8 Combining Qualitative and Quantitative Information

The relevant communication choice is often how to combine information types. A concrete example can help recipients understand and remember an aggregate regularity, while a statistical summary can place an individual case in perspective. The simulation intervention in Graeber et al.

(2024) illustrates one such complementarity: invented qualitative context makes the statistic's effect on beliefs more persistent without adding evidence. An open question is when a story supports the use of a statistic and when it instead displaces that statistic in judgment. Experiments that vary the representativeness of the example and measure both recall and the dynamics of beliefs could distinguish these possibilities.

5 IMPLICATIONS FOR THE SUPPLY SIDE OF INFORMATION

What does the evidence reviewed so far imply for the supply of information? Two margins are worth distinguishing. On the one hand, communicators can choose the form of evidence—for instance, a concrete story instead of an aggregate statistic (DellaVigna & Gentzkow, 2010). On the other hand, they can propose a narrative that gives this evidence a particular meaning.

The basic logic follows from Bayesian persuasion (Kamenica & Gentzkow, 2011): a sender designs an information structure to maximize the probability that a receiver takes a desired action. In light of the findings from the previous section, the type of information—e.g., whether the sender invokes a story or a statistic—becomes part of the persuasion design.

What are the potential advantages of stories over statistics? First, a sender can pick a story that is true but unrepresentative, and its persuasive force comes precisely from the audience's habit of generalizing from a compelling case study. Second, coverage permits selective emphasis: a sender can foreground attributes that favor the desired conclusion—such as a sympathetic protagonist or a vivid outcome—and omit unfavorable ones, all without stating a falsehood. Third, how the story is presented, e.g. its vividness, may boost encoding and recall.

Narratives offer an additional instrument of persuasion: by reshaping the recipient's understanding of how variables relate to one another (Eliaz & Spiegler, 2020; Schwartzstein & Sunderam, 2021), they can change how recipients interpret not only the evidence at hand but also evidence they encounter later.

Does empirical evidence support the importance of strategic incentives in shaping communication? Thaler et al. (2024) show that incentives to persuade rather than accurately inform increase the use of verbal rather than numerical descriptions of probabilities and effect sizes. This logic connects to a broader literature on media slant and strategic content selection (Gentzkow & Shapiro, 2010; Mullainathan & Shleifer, 2005). In our framework, media competition can be understood as competition over coverage and presentation: outlets choose which attributes to report and how to present them to maximize audience engagement (Capozza et al., 2026). Given the mechanisms reviewed in Section 4, these incentives can produce a systematic distortion in the public information environment.

6 OPEN CHALLENGES

While we argue that significant progress in understanding belief formation can be made by explicitly studying the impact of stories and narratives, doing so is far from straightforward. Stories are fundamentally qualitative in nature, rich, context-dependent, and resistant to the kind of standardization that empirical research typically demands. Together, these features pose a range of methodological challenges that any research program in this area must confront. In what follows, we describe what we view as the most significant of these challenges and discuss potential avenues for mitigating them.

6.1 The Measurement Problem in Qualitative Data

Qualitative information is often high-dimensional (Gentzkow et al., 2019; Ludwig & Mullainathan, 2024), posing challenges for constructing interpretable and valid measures. This high dimensionality also makes it hard to interpret treatment effects. For example, was the story effective because of the emotions evoked, because of its imagery or because the main character attracted so much attention? One way to tackle this identification challenge is to systematically annotate this data to explore heterogeneous treatment effects based on the coded features of text. Theory-driven coding schemes specify which features to extract, while human coders and large language models offer complementary ways to implement these schemes (Haaland et al., 2025). As Dell & Rambachan (2026) emphasize, credible inference with AI-generated variables requires explicit measurement criteria and appropriately designed validation.

To partly address this identification challenge, researchers can run experiments relying on controlled synthetic content. Such content can attempt to systematically vary structure, tone, or causal framing while holding factual content and arguments fixed. For example, Chopra et al. (2025) build a news app that aims to hold constant the news event and its core underlying factual claims while varying how the news is presented, e.g. in terms of the complexity or extent of opinion. Graeber et al. (2026b) vary the coherence of text, while holding the underlying facts and arguments constant. Both papers use human raters to validate that the LLM-generated versions hold the underlying facts constant.

6.2 Context Dependence

Qualitative content derives its meaning from contextual features and depends on people's prior beliefs. Cultural beliefs are an important part of this context, shaping which cases seem representative, which causal explanations seem plausible, and how particular experiences are interpreted (Nunn & Sanchez de la Sierra, 2017). For example, Nunn & Sanchez de la Sierra (2017) describe how beliefs in magical protection can persist despite combat deaths, because

these deaths are attributed to violations of the conditions required for protection. The same qualitative content can therefore induce sharply different responses across populations with different cultural beliefs.

This dependence on context poses a challenge for external validity: an intervention that changes beliefs in one population or setting may have little effect, or even the opposite effect, elsewhere because its meaning and perceived relevance differ. It also creates a tension with the use of minimalistic and abstract designs in experimental economics (Falk & Heckman, 2009), which facilitate experimental control and the isolation of mechanisms. Studying the belief impact of qualitative information often requires retaining the contextual features through which it acquires meaning. Such contextual richness need not undermine causal identification within an experiment, but it can make the resulting effect harder to attribute to specific features and harder to generalize. Measuring cultural beliefs and perceived causal relationships across settings could help explain when and why these effects generalize.

6.3 Rational Benchmarks for Belief Updating

A natural starting point for studying belief updating is the Bayesian benchmark, which serves as a rational reference point for how individuals should revise their beliefs when presented with new information. Under the Bayesian framework, rational agents update their priors by appropriately weighting the statistical informativeness of incoming evidence. For quantitative data, a large literature has documented systematic deviations from Bayes' rule (see Benjamin, 2019, for a review). This literature documents departures from rational inference and decision-making associated with base-rate neglect (Esponda et al., 2024), correlation neglect (Enke & Zimmermann, 2019), failures of contingent reasoning (Martínez-Marquina et al., 2019; Niederle & Vespa, 2023), neglect of alternative causes (Graeber, 2023), and cognitive constraints and simplifying heuristics in belief updating (Ba et al., 2025; Fan et al., 2026).

For qualitative information, however, constructing such a benchmark is inherently more difficult. The challenge is that the information content of qualitative statements is difficult to quantify in both lab and field settings, which makes it hard to define a Bayesian benchmark. One way to address this challenge in experiments is to explicitly and credibly declare the qualitative information as uninformative, as implemented in a robustness experiment in Graeber et al. (2024). While this approach allows the researcher to remain in a fully Bayesian framework, it may be somewhat artificial in many situations. Experiments on transparently debunked information offer another setting in which to construct such a benchmark. Musolff et al. (2026) compare the residual belief effects of debunked stories and quantitative signals. A complementary approach is to fully specify the data-generating process, so that examples provide no additional information about the distribution. Conlon & Kwon (2026) use this design to show that normatively irrelevant cues nevertheless shift beliefs, including when the examples depict explicitly impossible outcomes.

Their design rules out learning about an unknown distribution, while the relationship between cue effects and measured similarity supports an associative memory mechanism.

Depending on the research question, other approaches are feasible: Graeber et al. (2024) use respondents' immediate belief reaction as a subjective benchmark for perceived informativeness and exploit the absence of new information between elicitations to isolate memory-driven from processing-driven belief distortions. Graeber et al. (2026b) identify the effect of qualitative explanations compared to various benchmarks, including control conditions in which respondents merely learn about the action or the action and the confidence of the speaker. In addition, they conduct experiments in which a large language model merely changes the form of an explanation, while holding the underlying arguments and facts constant.

7 CONCLUDING REMARKS

Much of the information humans encounter is qualitative, such as stories and narratives, rather than quantitative. This review organizes different types of information along two dimensions. First, whether the provided information supplies new evidence or new interpretations. Second, whether the information provided is quantitative or qualitative.

We provide three main takeaways. First, learning from data and learning from models are distinct mechanisms that interact in important ways. Models shape the interpretation of subsequent evidence, while evidence can prompt model revision. Providing additional data and changing a subjective model are therefore different interventions, even when they target the same mistaken belief.

Second, qualitative information can bring to mind familiar experiences and associations. Mental simulation, attention, memory, processing fluency, and emotion can make qualitative information influential and persistent. Much of the evidence studies learning from stories and statistics. How these mechanisms affect learning from narratives relative to quantitative models remains an open question.

Third, strategic communication operates through both the selection of evidence and the choice of interpretation. Senders choose which cases or summaries to present and which relationships to emphasize in explaining them. Their influence can extend beyond a particular belief to the interpretation of future information. The consequences for accuracy depend on the representativeness of the evidence, the validity of the model, and the incentives governing their supply.

Some substantive questions about differences in learning from quantitative and qualitative information remain open. A crucial question is what drives the story–statistic gap. The evidence in Section 4.4 points to retrieval as the proximate channel, but it leaves open why statistics are less likely to be retrieved: because they receive less attention when first encountered, because

they are encoded with fewer contextual associations, or because later situations provide fewer cues that bring them back to mind. Designs that independently manipulate attention at encoding and retrieval cues at the time of judgment could separate these channels.

Beyond individual cognition, there remain open questions about the social transmission of stories and narratives (Shiller, 2017). Stories and narratives evolve as they are transmitted (Graeber et al., 2026a), with selection pressures determined by attention, emotion, and incentive structures. Future work could examine which linguistic or emotional features make stories more likely to go viral, how media competition affects the evolution of shared stories, and when market incentives amplify distortions. A complementary direction concerns *vertical* transmission: stories and narratives passed across generations may be a key vehicle through which culturally transmitted beliefs persist, as documented for the role of environmental stability in sustaining tradition (Giuliano & Nunn, 2021).

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