Whom do we learn from?

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Abstract

This paper studies how the identity of an information source influences learning, and reports from four large-scale online experiments designed to disentangle identity preferences from beliefs about the quality of an information source. The experiments examine both naturally occurring identities (caste and religion in India) and experimentally assigned identities (in an EU/US sample). Across identity contexts, there is no evidence that preferences for the identity of an information source influence social learning. On the other hand, beliefs about information quality strongly influence learning, but participants are overconfident and often do not learn when it would benefit them. Finally, participants prefer to learn from a non-social source (a computer algorithm) rather than another human. The results highlight the importance of providing credible signals of information quality, especially when social identities are salient.

Keywords: Social learning, Social identity, preference identification, algorithm appreciation
JEL Codes: D83, D91

1 Introduction

Social learning is fundamental to human evolutionary success (Boyd et al., 2011; Henrich, 2016) and influences many economic decisions (Mobius and Rosenblat, 2014). In social learning, decision-makers (DMs) extract information by observing others' actions and decide how to use that information. When DMs observe others' actions, they may also notice other attributes such as a person's race, religion, or gender – components of social identity. While a large body of research has shown that social identity affects many economic decisions through both beliefs and preferences (Tajfel and Turner, 1978; Akerlof and Kranton, 2000; Shayo, 2020; Charness and Chen, 2020), the links between identity and learning are relatively unexplored. This paper addresses that gap by examining the channels through which identity influences learning in different identity contexts.

When learning from others, DMs may use a source's identity to form beliefs about information quality, as in statistical discrimination (Phelps, 1972; Arrow, 1973). This suggests that the salience of identity could increase learning and improve decision-making in situations where observing information quality is difficult. At the same time, DMs may have preferences for associating with or avoiding particular identity groups, as in taste-based discrimination (Becker, 1957; Guryan and Charles, 2013). This preference channel could lead to poorer decision-making as individuals would ignore information not because of its quality but because of the identity of its source. Such behaviour not only undermines effective communication but could also lead to belief polarisation or the formation of echo chambers at scale (Levy and Razin, 2019). Therefore, understanding these channels is crucial for designing communication strategies and information interventions to improve decision-making. However, identifying preferences for the identity of information sources is empirically challenging as identity is often correlated with many determinants of information quality, such as income or education.

In this paper, I report on four incentivised online experiments (with $N = 2297$ participants) designed to disentangle beliefs about information quality from preferences for the information source's identity. The experiments share the same structure – a two-period task in which participants make incentivised decisions in both periods – and are deployed in different identity contexts. In the first period, participants make an independent decision in a cognitively demanding "balls-and-urns" task – a well-established paradigm for examining belief formation and learning (Benjamin, 2019; Weizsäcker, 2010) – where selecting the correct decision is required to earn an incentive. In the second period, participants are shown a decision made by another individual – the *source* – on the same task. Participants then decide whether to learn from the source by *switching* to the source's decision, or not to learn by *sticking* to their independent decision.

This experimental framework focuses on an understudied type of learning in which decision-makers choose to learn from others despite having access to identical information. Both the decision-maker and the source make choices on the same task with the same information – information that is sufficient to yield an incentive-maximizing decision – and they operate under identical incentive structures. This setup provides a rational benchmark: fully informed Bayesian decision-makers would always make a correct decision in the first period and therefore have no reason to switch in the second. Consequently, a decision to switch in the second period cannot be attributed to a belief that the source possesses superior information – usually the focus of social learning experiments – but must instead

reflect a belief that the source has a better interpretation of the same information. Understanding this form of learning is crucial because many real-world decisions involve seeking not only better information but also more effective interpretations. For example, when choosing a health insurance or investment plan, DMs may choose to follow the decisions of their friends or peers despite having exhaustive information about the various options.

Decoupling identity-driven beliefs and preferences is achieved by manipulating two attributes of the source. First, participants receive a signal of the information's *quality*, which is the probability that the shown source's decision is correct. It represents the probability with which switching to the source would yield the incentive, and is randomly assigned. Second, they observe the source's social *identity*, which is also randomly assigned and varies between treatment conditions in each experiment. As the quality signal is independent of the source's identity, comparing switching behaviour between treatments reveals preferences for the source's identity.

Together, the four experiments provide a dataset of ≈ 13400 switching decisions made by 2297 participants. Two experiments study naturally occurring identity contexts, caste and religion in India. These factors play a central role in Indian social and economic life (Munshi, 2019; Mosse, 2019; Iyer, 2016). A person's religion or caste is often salient as it can be accurately inferred from their name, mode of speech, body language, or other visible markers. In experiment *Caste*, the source belongs to either a high-status or low-status caste group. In experiment *Religion*, the source is either Hindu or Muslim. Because participants also have religious and caste identities, the design allows for the analysis of both general preferences – whether the DM learns more from a source of a particular caste or religion – and in-group preferences – whether the DM learns differently from a source sharing their religious or caste identity. Prior research indicates that identity also influences decision-making through in-group favouritism and out-group parochialism (Shayo, 2020), and the analysis examines these effects in detail.

Experiment *Minimal* focuses on in-group preferences using experimentally assigned identities. The experiment is based on the Minimal Identity paradigm (Tajfel and Turner, 1978; Chen and Li, 2009) – participants are randomly assigned to one of two minimal identity groups and see a source from either their in- or out-group. This paradigm allows for the study of identity effects without invoking many of the empirical challenges associated with naturally occurring identities (Charness and Chen, 2020).

Finally, experiment *Human vs. Computer* compares learning from social versus non-social sources by presenting participants with decisions made either by a human or by a computer algorithm. This experiment addresses the increasingly important question of whether individuals learn differently from algorithmic recommendations or generative AI tools than from other humans. Participants in the *Minimal* and *Human vs. Computer* experiments are recruited via an online labour platform, and are from the EU/US.

Turning to the results, I first examine how beliefs about information quality shape learning behaviour. The analysis shows that participants are responsive to the randomly assigned quality signal: the propensity to switch increases with an increase in information quality. However, most participants leave money on the table by not switching even when the source is high-quality. This behaviour is partially explained by participants' over-confidence – more confident participants learn less, and overall,

individuals overestimate the accuracy of their initial decisions. These patterns are consistent across all samples and identity contexts, though responsiveness to information quality varies.

The second main finding is that people do not express a preference for learning from a particular identity in the *Caste*, *Religion*, and *Minimal* experiments. Participants are equally likely to switch to a source from a high- or low-status caste group in experiment *Caste*, a Hindu or a Muslim source in experiment *Religion*, or an in-group or out-group source in experiment *Minimal*. Additional analyses using self-reported religious and caste identities reveal no differences in switching behaviour when decision-makers share the source's identity compared to when they do not. Several robustness tests and heterogeneity analyses – examining biases in belief updating, exposure to religious and caste diversity, and attitudes toward caste-based affirmative action – further support these null results. Although there is weak evidence of preferences for certain overlaps between religious and caste identities, overall, the results strongly suggest that participants do not have a systematic preference for the identity of information sources when those sources are human and their identities are salient.

Finally, the third main result is that people prefer to learn from a non-social source (a computer algorithm) rather than from a social source (an anonymous human). Participants in experiment *Human vs. Computer* are 15% points more likely to switch to the source when the source is a computer than when it is a human. The effects are quantitatively large (about 0.3 standard deviations) and are the same at both low and high levels of information quality. This result supports "algorithmic appreciation", a general preference for learning from a non-social source than from another human.

This paper makes two contributions to the empirical social learning literature (reviewed recently by Mobius and Rosenblat (2014)), in which the role of the identity of information sources has been largely overlooked. First, the results show that beliefs about information quality strongly influence learning, while preferences for specific identities or for their in-groups. This finding complements experimental research documenting identity-based differences in information processing – such as gender differences in household social learning (Conlon et al., 2021), political in-group biases (Robbett et al., 2023; Zhang and Rand, 2023)), national in-group following (Dekel and Shayo, 2023), effects observed with the minimal identity paradigm (Berger et al., 2018; Parys and Ash, 2018; Zou and Xu, 2022), and evidence from agricultural technology adoption (BenYishay and Mobarak, 2018) – but has not identified whether these effects are driven by beliefs or preferences related to identity. The dominance of the belief channel is consistent with findings on information quality (Robbett et al., 2023) and perceived knowledge (Dekel and Shayo, 2023). The results contrast, however, with those of Bauer et al. (2023), who find evidence of preferences for information from political in-groups.

Second, the experiments in this paper provide a novel perspective on learning by focusing on situations where all stakeholders have the same information and incentives. The results show that a sizeable share of people choose to learn from others even though a rational benchmark suggests that switching is never beneficial. This behaviour cannot be explained by a taste for conformity (Goeree and Yariv, 2015) as switching responds to increases in source quality. The patterns highlight a potentially powerful source of learning where people seek better interpretations of the same information, a mechanism that can influence learning even when information sets differ.

This paper also speaks to research on the economics of identity, in particular to the literature focusing on social identity in India, by providing direct evidence of the influence of religion and caste

on learning. Caste and religion are important aspects of social life and economic behaviour in India (see Munshi (2019); Mosse (2019); Iyer (2016) for reviews), and a large body of prior research has documented the influence of religious and caste identity in various decision-making domains such as consumption (Atkin et al., 2021), hiring in labour markets Siddique (2011), labour supply (Cassan et al., 2019; Oh, 2023), marriage markets (Banerjee et al., 2013), and teamwork (Ghosh, 2022). This paper studies the role of caste and religion on learning, and shows that preferences for the religious or caste identity of information sources may not affect learning when the quality of information is salient. The results also show systematic differences in beliefs about the abilities of different caste and religious groups, and suggest that these beliefs may be used to infer information quality when the latter is not observable.

Finally, this paper contributes to research on human-computer interaction by comparing social and non-social learning. This literature has previously found mixed results: while some have found that people are averse to learning from algorithms and favour learning from humans (Goeree and Yariv, 2015; Dietvorst et al., 2018, 2015), others have found that people display algorithm appreciation by favouring algorithms over humans in certain situations (Logg et al., 2019). More recent research shows that these differences may depend on contextual features of decision tasks Hou and Jung (2021) or nomenclature Langer et al. (2022). This paper's results show evidence for algorithm appreciation, suggesting that when information quality is precisely known, people prefer to learn from a non-social computer algorithm than from another human.

The paper is organised as follows: Section 2 presents the experiment design, provides intuition for the identification and hypotheses, and describes the various experiments and identity contexts. Sections 3 examines the causal role of beliefs using the experimental variation in source quality. Section 4 focuses on causal evidence of preferences on learning, supported by robustness tests and heterogeneity analyses. Section 5 concludes with a discussion of the results and open questions for future research.

2   Experiment Design

The study consists of four main experiments, each with two treatment conditions. Participants in an experiment are randomly assigned upon entry to one of two treatment conditions which differ only in the identity of the source. All experiments use the same task structure, but differ in the identities used and the manner in which the identities are made salient.

This section starts with a description of the common experiment structure, followed by a conceptual discussion, and then presents the details of the different identity contexts of each experiment along with relevant background information. A complete set of screenshots of the experiment are presented in Appendix D.

2.1   Experimental task

The experimental task builds on the "balls-and-urns" paradigm, which is widely used to study belief formation and social learning. Participants complete six tasks where each task takes place in two

periods and participants make an incentivised decision in each period.

First period. Participants are shown two urns, urn A and urn B, which contain 100 red or black coloured balls. Urn A contains θ red balls, and urn B contains $100 - \theta$ red balls. Urn A is randomly selected with probability p and the participant does not know which urn is selected. k balls are drawn (with replacement) from the chosen urn and shown to the participant. Participants use a slider to make an incentivised decision $y_1 \in (0, 100)$ of the probability that urn A was chosen. After making the decision, participants state their confidence that y_1 is within $\pm 2\%$ of the correct decision. The tasks are pre-defined in the sense that the values of the base rates p, urn composition θ, and the signals (colours of k drawn balls) are the same for all participants. This design choice ensures that participants are exposed to tasks of the same difficulty and eliminates several practical challenges. Participants see tasks in a randomised order. The tasks, corresponding parameters, and other details are listed in Appendix Table B.1.

Participants can calculate the correct answer for each task by applying Bayes' rule using the provided information.[1] Participants are aware of this: they are given detailed instructions and work through a training task on how to use Bayes' rule to calculate the correct answer; in free-text responses, many participants indicated that they tried to apply Bayes' rule while working on the task. However, the task is cognitively demanding which means that learning from others may be beneficial; participants have an opportunity to do so immediately after they make their first-period decision.

Second period and main outcome. Participants are shown a decision $y_s \in (0, 100)$ made by another person, the source s, on the same task. Participants know that the source had the same information and saw the same draws. Participants see (i) the group *identity* g of the source, which is randomly assigned between-subjects, and (ii) a signal Q of the *quality* of the decision. Figure 1 shows the representation of these elements in the experiment interface. Next, participants make an incentivised binary choice y_2: whether to *stick* to their first decision ($y_2 = y_1$) or *switch* to the shown decision ($y_2 = y_s$). This is the main outcome variable, *Switch*, which is 1 when $y_2 = y_s$ and 0 when $y_2 = y_1$.

Source Decisions. Each task has two source decisions associated with it. One of these decisions is correct and the other is incorrect. These decisions were extracted from the incentivised first-period decisions made by participants in separate experiments (conducted with an Indian sample and on Prolific). The decisions were chosen to satisfy a few criteria, the most important of which was that each of these decisions was made by at least one person from each identity group. Table B.1 provides a list of the correct and incorrect source decisions for each task. Additional details on how the sources are curated are provided in Appendix C.3.

Quality signal. Participants are given a signal of the quality Q of the source's decision which is the probability that y_s is the correct decision. This means that with probability Q participants

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[1] The correct answer can be calculated as follows: Let the number of drawn red balls $= r$. Then, $P(\text{draws}|A) = \binom{100}{k} \cdot \frac{\theta}{100}^r \cdot \frac{100-\theta}{100}^{k-r}$, $P(\text{draws}|B) = \binom{100}{k} \cdot \frac{100-\theta}{100}^r \cdot \frac{\theta}{100}^{k-r}$, and finally, $y_T = P(A|\text{draws}) = \frac{p \cdot P(\text{draws}|A)}{p \cdot P(\text{draws}|A) + (1-p) \cdot P(\text{draws}|B)}$

Figure 1: Source – Attributes

The computer shows:
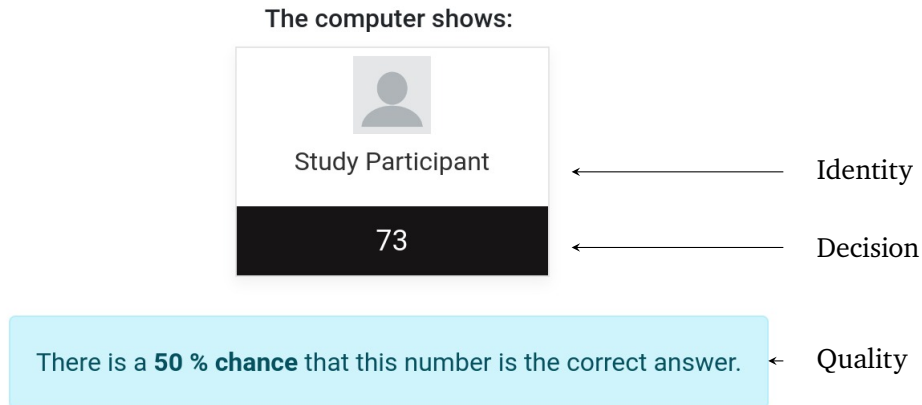
Notes. The figure shows how the source is represented in the experiments. *Identity* is randomly assigned between-subjects within each experiment group. The *quality* of the source's decision is randomly assigned at the task-level, and is the probability with which the shown *decision* is objectively correct ($= y_T$).

are shown a correct decision, and with probability $100 - Q$, participants are shown an incorrect decision. The quality varies within-subject and is chosen randomly for each task: $Q \in \{0.5, 0.9\}$ in *Caste*, or $Q \in \{0.5, 0.6, 0.7, 0.8, 0.9\}$ in the other experiments. This signal provides participants with precise beliefs about the quality of the decision that they could choose to learn from, and achieves the objective of making information quality independent of the source's identity. Additional details on these signals are provided in Appendix C.4.

Incentives. Participants complete six tasks, and make two decisions in each task. Each task has different configurations of balls, urns, and associated probabilities. One of the 12 decisions is randomly chosen for a bonus reward. Participants get a \$3 bonus payment if the chosen decision is within $\pm 2\%$ of the true posterior; otherwise, they get no bonus. This incentive scheme was chosen both for simplicity, and to avoid skewing participant decisions as highlighted in recent literature (Danz et al., 2022). All participants received a flat \$2 fee for participating in the study. Participants were paid in cash or in "channel points" with a value equivalent to the stated dollar amounts.

2.2 Conceptual framework

In these tasks, a decision maker (DM) must choose the correct decision y_T in order to earn an incentive. Although the DM has sufficient information to identify y_T, the cognitive demands of the task mean that a non-Bayesian DM may find switching to the source's decision beneficial. In contrast, a fully Bayesian DM would identify the correct decision immediately and would have no incentive to switch.

The DM's decision to switch is a function of the their beliefs about the quality of the information provided by the source and their confidence in the accuracy of their initial decision. The DM would be more likely to switch if they believe that the source provides high quality information, and less likely

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to switch the more confident they are about their independent decision's accuracy. At the same time, switching might involve psychological costs which would cause DMs to prefer their initial decisions. Prior research supports this view, showing that individuals tend to update their beliefs conservatively (Benjamin, 2019) and resist incorporating new information (Weizsäcker, 2010; Conlon et al., 2022).

Therefore, DM's switch if the utility from switching exceeds the utility from sticking:

$$U(E[y_2 = y_s], k) > U(E[y_2 = y_1])$$

where k represents the cost of switching or a preference for sticking to the initial decision. In the experiment, the expected values of switching or sticking are only affected by DM's beliefs about the quality of the source's information ($E[y_2 = y_s]$) and their own decision's accuracy ($E[y_2 = y_1]$). This framework generates two empirically verifiable predictions relating to beliefs:

Prediction.

1. *Switching increases with an increase in beliefs about information quality (Q).*

2. *The more confident DMs are about the accuracy of their first decision (y_1), the less likely they are to switch to the source.*

DMs also observe the identity, g, of the source, which can affect these beliefs and preferences. First, the DM may make inferences about the source's task-relevant abilities based on perceived characteristics of the source's social groups, in a form of statistical discrimination (Phelps, 1972; Arrow, 1973). If a DM holds prior beliefs about the ability associated with a particular identity group, these beliefs influence their assessment of the source's decision quality. Consequently, DMs respond differently to sources of varying identities, driven by differences in these group-related beliefs. If these beliefs are incorrect, the DM's behaviour could resemble inaccurate statistical discrimination (Bohren et al., 2023).

Second, the DM may have a preference for (or aversion against) learning from sources of specific identities. Building on theories of taste-based discrimination and social identity research (Becker, 1957; Guryan and Charles, 2013; Akerlof and Kranton, 2000), which posit that membership to an identity group motivates decision-making to align with identity-driven behavioural prescriptions, the salience of social identity might lead individuals to ignore information not because of its quality but because of the identity of the source. In other words, the cost (preference) of switching k_g may vary based on the source's identity. If the DM experiences aversion or identity-driven social pressures against associating with a particular group, switching becomes relatively costly. Conversely, affinity for a particular group reduces the cost of switching.

The goal of the experiment is to causally identify whether k varies based on the source's identity. The main empirical challenge is that both preferences for switching to sources of particular groups and beliefs about groups jointly determine whether the DM chooses to switch. Thus, to identify preferences for the identity of information source, beliefs about the quality of information must be controlled so that they are independent of identity. This is achieved through the random assignment of the quality signal Q, which breaks the link between beliefs about information quality and identity. Because this signal is precise and exogenously assigned, any observed differences in switching

Table 1: Experiment overview

Experiment	Identity Treatment	Sample	Sample size	Identity salience	Dates
Religion	*H* – Hindu	Panel survey	431	Surnames	April 2023
	M – Muslim		422		
Caste	*G* – General	Panel survey	415	Surnames	September 2023
	O – SC/ST/OBC		436		
Minimal identity	In-group	Prolific	142	Klee-Kandinsky	March 2023
	Out-group		136		
Human vs. Computer	Computer	Prolific	163	Labelling	March 2023
	Human		430		

Notes. Participants are assigned to one experiment, and to one identity condition within each experiment. General – Source is from the General caste category. SC/ST/OBC – Source is from the Scheduled Castes, Scheduled Tribes, or Other Backward Classes categories. In treatment *Human*, the sample from the *Minimal* experiments is also used. Appendix Table B.2 provides information on the demographics of the different samples.

because of a difference in the source's identity can be attributed to preferences (or different costs) for learning from one group relative to another.

2.3 Identity contexts

Participants in an experiment are randomly assigned upon entry to one of two treatment conditions which differ only in the identity of the source. Table 1 provides a list of experiments in this study. Appendix Table B.2 provides summary statistics of the demographics of the different samples.

Experiment *Caste*

Background information. Caste is an ancient system of social stratification in India that consists of thousands of caste groups called *jatis*. A person's caste is largely determined by birth. Many prominent features of the caste system such as endogamy, social hierarchy, segregation, and ritual purity continue to influence modern Indian society (Mosse, 2019; Munshi, 2019). Caste groups are often associated with occupations (Cassan et al., 2019) – For example, some castes are perceived as intellectuals, some as entrepreneurial or business-oriented, and others as farmers, etc. Some specific occupations are associated with population groups which were historically excluded from the caste system and regarded as "untouchables". While the caste system is largely linked with Hinduism, non-Hindus may also hold caste identities. To effectively target welfare programs and affirmative action policies, the Government of India classifies castes into four "categories". The "General" category (also known as the Forward Castes, ≈ 30% of the population) consists of *jatis* that are considered socially and economically advanced (in relative terms). The "Scheduled Castes" (SC, ≈ 20%) and "Scheduled Tribes" (ST, ≈ 9%) categories are formed of castes that are the most economically and socially disadvantaged. This category also contains the erstwhile "untouchables" or *Dalits,* and people from indigenous tribes. Last, the "Other Backward Classes" (OBC, ≈ 40%) category contains many *jatis* that are economically and socially disadvantaged relative to the General category.

Caste identity can influence both beliefs and preferences about information quality. First, indi-

viduals may hold beliefs about the cognitive ability of people belonging to particular caste groups. This could be driven by economic realities such as disparities in education and income between caste groups, or by caste-specific stereotypes related to occupational and educational choices. Second, people have strong preferences for associating with others from their caste groups or for avoiding associating with caste groups considered lower in status. Such caste-dependent preferences could impact how people use information from sources belonging to different castes.

Implementation. In this experiment, the caste identity of the source is made salient through surnames that are informative of the caste category of the individual. These surnames are shown along with an arbitrarily chosen initial (for example, Mr A. Moorthy) in place of "Study Participant" in Figure 1. There are two treatments in this experiment: G and O. In treatment G, surnames belonging to the General (or "Forward Castes") category are used. In treatment O, surnames belonging to the Scheduled Castes, Scheduled Tribes, or Other Backward Classes (SC/ST/OBC) are used. The surnames were validated for recognisability through a separate survey conducted through the same provider.[2] A list of surnames and additional details are presented in Appendix C.

The *Caste* experiment and the validation study were conducted through online surveys with a gender-balanced sample of Indian Hindu participants recruited through an online panel survey provider. The effective sample size for the main experiment is 851 Hindu participants. $\approx 63\%$ of the participants belonged to the General (G) caste, and the remaining $\approx 37\%$ belonged to one of the other caste groups. The G category is over-represented in the sample relative to the general population.

A supplementary experiment, *Caste – No Signal*, was conducted at the same time as the *Caste* experiment. The only difference between these two experiments was that participants in *Caste – No Signal* did not receive a quality signal in the second period.

Experiment *Religion*

Background information. Religion is an important part of daily life in India.[3] $\approx 80\%$ of the country is Hindu, $\approx 14\%$ is Muslim, and the rest of the population follows other religions such as Christianity, Sikhism, Buddhism, Jainism, etc (Census, 2011). Religion moderates social and market interactions, and inter-religious relations are often characterised by a lack of trust. In particular, tensions between Hindus (the majority religion) and Muslims (the largest minority) have deep historical roots which were exacerbated during the British colonial period and the eventual Partition of India in 1947. Contemporary conflicts arise from a variety of factors such as territorial disputes, religious nationalism, political polarisation, and competition for resources (Iyer, 2016; Iyer and Shrivastava, 2018; Jaffrelot, 2021). A recent study by the Pew Research Center (2021) finds that $\approx 21\%$ of Muslims and 17% of Hindus report having experienced discrimination because of their religion in the past 12 months.

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[2] ≈ 350 individuals were incentivised to correctly classify a list of surnames into one of the four caste categories.

[3] Two-thirds our sample say that religion is a very important part of their daily lives, and 90% say that it is either somewhat or very important. This echoes findings from other surveys like the Gallup World Poll and the World Values Survey.

Muslims are, on average, poorer and less educated than Hindus (Asher et al., 2024), which may lead to beliefs that Muslims are less likely to be well-educated than upper-caste Hindus and therefore less likely to perform well on the balls-and-urns tasks. In terms of preferences, research has provided evidence of taste-based discrimination in the labour market (Thorat and Attewell, 2007), and that religious identity affects trust and pro-sociality (Dhami et al., 2024). Thus, it is plausible that religion can affect social learning through both belief and preference channels.

Implementation. The religious identity of the source is made salient using surnames that are informative of the religion of the individual. In treatment *Hindu*, the names are the same as those used in the *G* treatment of the *Caste* experiment. In treatment *Muslim*, the surnames are common Muslim surnames. The Muslim surnames were not validated separately as these are generally easily identifiable by Indians. A list of surnames and additional details are presented in Appendix C.

This experiment was conducted through online surveys with a sample of participants from India provided by an online panel survey provider. The effective sample size is 853 participants, of whom 647 were Hindus ($\approx$ 75%), 67 Muslims ($\approx$ 8%), and the rest ($\approx$ 17%) of other religions. Muslims are under-represented in the sample relative to the population.

Experiment *Minimal Identity*

Background information. The minimal identity paradigm that has been used for decades by social scientists to study the effects of identity on various decisions (Tajfel et al., 1971; Chen and Li, 2009). Participants begin by making choices in an innocuous task, often choosing between paintings by the artists Wassily Kandinsky and Paul Klee. These choices are used to classify participants into arbitrary groups unrelated to naturally occurring identities. Research has demonstrated that this method induces people to behave in a "groupy" manner by making choices that favour their in-group over their out-group (see Charness and Chen (2020)). The method has been used to study in-group effects in learning, although the focus has been on learning in settings with private information: for example, Berger et al. (2018), Parys and Ash (2018), and Zou and Xu (2022) find that people learn more from their in-groups in experimentally assigned identity settings. An unanswered question is whether these documented effects are driven by beliefs or preferences.

Implementation. In experiment *Minimal*, I follow the method used in Chen and Li (2009) to assign minimal identities to participants. First, participants are asked to examine a few pairs of paintings and indicate which they preferred in each pair.[4] Next, participants are classified into either the Orange or Purple group based on whether they liked Klee (Orange) or Kandinsky (Purple) paintings. Participants are informed of the method by which the groups were assigned. Participants are also reminded of their assigned group identity halfway through the six tasks. Participants see sources as in Figure 1 with the addition of an orange or purple coloured label with the text "Orange group" or "Purple group", which depends on the participant's group and the treatment to which they are

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[4]One of the paintings in each pair was created by the artist Paul Klee, and the other by the artist Wassily Kandinsky. Paintings by these artists have been used in many studies that use this method because of their similarity (at least, to the untrained eye).

assigned. In the *In-group* treatment, they see sources belonging to the same group and in *Out-group* they see sources from the other group.

Participants in this experiment were recruited through Prolific (a popular survey platform for social science experiments) and came from the US, UK, and EU. The effective sample size is 278.

Experiment *Human vs. Computer*

Background information.   Understanding human-computer interaction has become increasingly important with developments in generative artificial intelligence and the general importance of the internet as a medium in all aspects of social and economic life. However, the evidence on whether people learn more from humans or computers is mixed. While some find that people are averse to learning from algorithms than from other humans (Goeree and Yariv, 2015; Dietvorst et al., 2018, 2015), others find evidence of algorithm appreciation (Logg et al., 2019). Hou and Jung (2021) show that appreciation or aversion emerges because of differences in framing and perceived accuracy, and Langer et al. (2022) document the sensitivity of people's responses to the terminology used to refer to the non-social source. The *Human v. Computer* experiment studies whether differences in how people learn from humans and algorithms sources is driven by preferences for non-social sources.

Implementation.   In this experiment, participants see either an anonymous human or a "Computer". In treatment *Computer*, the source is labelled as "Computer", and the human icon is replaced with a computer icon. The comparison group for this treatment are participants pooled from a separate treatment within this experiment (*Human*, where sources are labelled as "Study Participant" as in Figure 1) and responses from the minimal group experiment.[5]

Participants in this experiment were recruited through Prolific, and the effective sample size is 593.

Study details and procedures

The experiments were programmed using OTree (Chen et al., 2016). The experiments on Prolific were conducted in March 2023. The *Religion* experiment was conducted in collaboration with Faktum Research in April 2023. The *Caste* experiments were conducted in September 2023 in collaboration with Norstat. The experiments were pre-registered at the AEA RCT registry (#0011066 and #0011924). All experiments were reviewed and approved by the IRB at the Norwegian School of Economics (NHH-IRB 39/22 and 44/22).

Participants were allowed to participate in the incentivised tasks only if they passed two attention checks and correctly answered a battery of comprehension questions. Participants are given two opportunities to pass the test. The pass rate in the *Religion* and *Caste* experiments is about 25%, and about 45% in the Prolific experiments. Participants also respond to a series of questions including demographic characteristics, religiosity, attitudes towards caste-based affirmative action, exposure to people from other castes/religions, and beliefs about the abilities of different caste/religious groups on the experimental task in the *Caste* experiment. Details are presented in Appendix C.

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[5]This was pre-registered, under the condition that the treatment effects in *Minimal* were minimal.

In 2.2% of the decisions, participants' first-period decisions were the same as the source's decision. As the motive behind the second-period decision cannot be clearly attributed in such cases, these decisions are excluded from most of the analyses reported in this paper.[6]

2.4   Descriptive Patterns

This part of the paper presents aggregate patterns in participants' task behaviour in the experiments.

First-period performance.   The bars in Panel (a) of Figure 2 show the fraction of first-period decisions that are objectively correct (incentive-yielding, within ± 2 of y_T) in each experiment. The share of correct decisions ranges from $\approx 12\%$ in the Religion experiment to $\approx 14 - 15\%$ in the other experiments. Thus, while some participants make accurate decisions, most participants stand to improve their outcomes if they choose to switch in the second period. These patterns also show that learning from others in this situation could be useful, fulfilling one of the design goals.

Second-period behaviour.   The bars in Panel (b) of Figure 2 show the fraction of participants who choose to learn by switching to the source in each experiment group. The triangles in the plot represent the fraction of participants who would improve their outcomes (i.e. earn more money) if they chose to switch. The figure shows that while a considerable fraction of participants switch (ranging from $\approx 24\%$ in the Religion experiment to $\approx 43\%$ in the Human vs. Computer experiment), a lot of participants leave money on the table by sticking with their own decision rather than switching to the source in the second period. Appendix Figure A.1 shows the distribution of the fraction of switching decisions in each experiment group. The figure shows that in all experiments, a small fraction of participants always switch, and in 3 of the 4 experiments, the modal participant never switches.

3   The Role Of Beliefs

This section presents experimental evidence on the role of beliefs about the quality of information on learning, focusing on testing the predictions of the conceptual framework.

Participants in the experiment receive a signal about the quality of the information provided by the source, which is the probability that the shown decision is correct. This is randomly assigned for each task and varies between 50% and 90%. Figure 3 shows the proportion of switch decisions at each level of the quality signal, separately for each of the experiments. As the quality of information increases from 50% to 90%, switching in the *Caste* and *Religion* experiments increases by $\approx 6\%$ points and by $\approx 30\%$ points in the *Minimal* and *Human vs Computer* experiments. The figure shows that the prediction holds in all experiments – participants are more likely to switch when quality is higher. The responsiveness to an increase in quality varies across samples and is more pronounced in experiments *Minimal* and *Human vs Computer*.[7]

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[6]The results are unaffected when these observations are included, and when the exclusion window is expanded to within ± 2.

[7]Appendix Figure A.2 reproduces this figure controlling for the treatment condition to which participants

Figure 2: Descriptive patterns: Task performance and switching rates.

(a) First period: Decision accuracy

(b) Second period: Switching
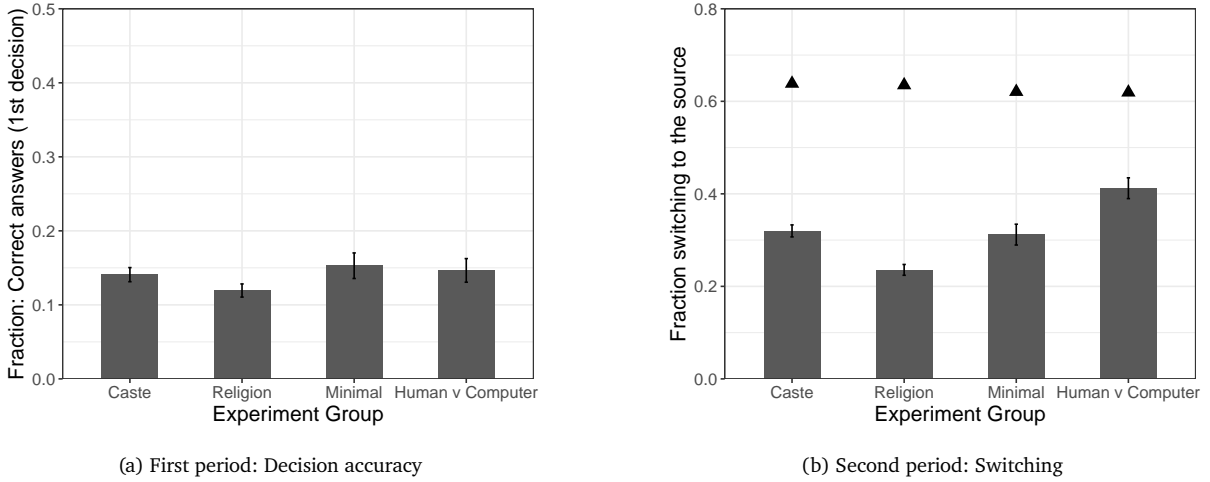
Notes. Panel (a) Bars indicates the fraction of decisions where participants make an incentive-yielding decision in the first period in an experiment group. (b): Bars indicate the fraction of participants who chose to switch to the source in the second period in an experiment group. Triangles indicate the fraction of decisions where switching to y_s would have been incentive-yielding. Error bars indicate 95% confidence intervals.

The figure also shows that switching is relatively low even when information quality is high – when the quality of the shown information is 90%, switching ranges from $\approx 36\%$ to $\approx 53\%$ in the different experiments. These patterns suggest that participants find switching costly, and are consistent with the findings from Weizsäcker (2010) and Conlon et al. (2022) which have documented that people do not learn from others even though they would benefit by doing so.

This behaviour may be partially driven by over-confidence. The median participant reports a confidence level of $\approx 85\%$ in the Caste and Religion experiments and $\approx 70\%$ in the Minimal and Human v. Computer experiments that their first-period decision will earn the incentive. Participants behave in line with these beliefs: Panel (a) of Figure 4 shows that more confident people make smaller errors (measured by the difference between their first-period decision and y_T). Panel (b) of Figure 4 shows that more confident people are less likely to switch in the second period. Further, Appendix Figure A.3 shows that participants switch more when information quality is higher than their confidence in their own decision. The figures also show that these patterns are consistent across experiments.

Performance beliefs: Identity groups. In a separate survey ($N = 327$) conducted with Indian participants in July 2023, I elicited incentivised beliefs about the likelihood that a randomly chosen General Caste, Scheduled Caste, or Muslim individual would make an accurate first-period decision.[8] Most participants vastly overestimate the likelihood of success of all identity groups. For example, high caste status Hindus believe that the likelihood of success is 76.6% for fellow high-status Hindus, 71% for low-status Hindus, and 61.7% for Muslims. These beliefs are much higher than the

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are randomly assigned, and shows virtually the same patterns.

[8]Participants in this survey only made first-period decisions on a single task, and thus were not exposed to sources.

Figure 3: Effect of beliefs about information quality on learning
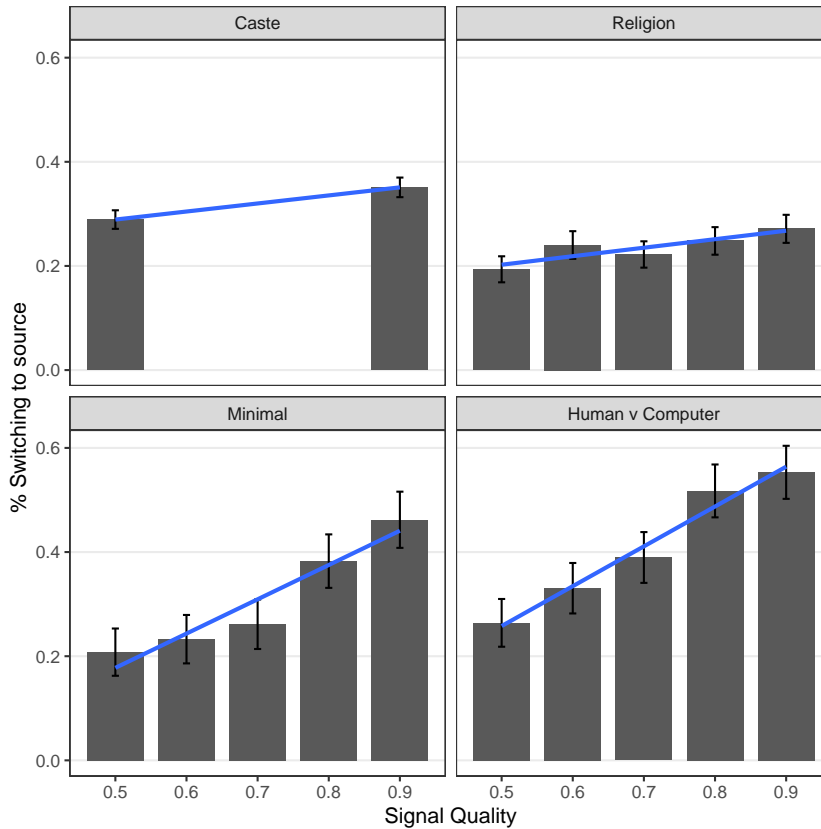
Notes. The graph shows the fraction of decisions where participants choose to switch to the source in each experiment, at each level of source quality Q. $Q \in \{50, 90\}$ in *Caste*, and $Q \in \{50, 60, 70, 80, 90\}$ in the other experiments. Error bars indicate 95% confidence intervals.

actual success rates of about $\approx 12 - 13\%$. Figure 5 plots the cumulative distribution of these beliefs and shows that participants believe that people of different castes and religions differ in task performance. Panel (a) shows that participants believe that the *G* category outperforms the *O* category, and Panel (b) shows that participants believe that Hindus outperform Muslims.[9]

Beliefs without the quality signal.   A supplementary experiment, *Caste – No Signal*, was conducted concurrently with experiment *Caste*. The only difference between these experiments was that participants were given a quality signal in the *Caste* experiment, but not in *Caste – No Signal*. In both experiments, participants were incentivised to provide their beliefs about the performance of the General and the SC caste groups after completing the main tasks (using the same question as in the beliefs survey discussed above). Appendix Figure A.4 presents binned scatter plots of switching on participants' beliefs about the performance of a random individual from the caste group of the treatment to which they were assigned (either from the General category, or the Scheduled Castes category). The left panel of Appendix Figure A.4 shows that when the quality signal is not provided, switching increases with the participant's beliefs about success. The right panel of Appendix Fig-

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[9]The p-values from two-sample Kolmogorov-Smirnov tests for the equality of distributions are < 0.01 in both cases.

Figure 4: Confidence: Task performance and switching

(a) First period: Accuracy   (b) Second period: Switching
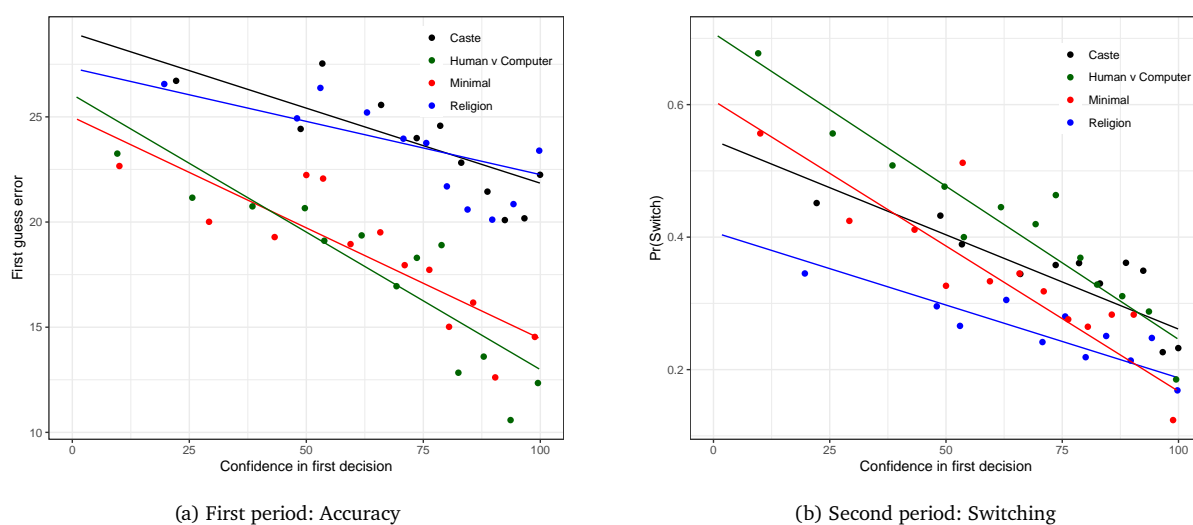
Notes. Binned scatter plots showing the relationship between the participant's stated confidence in the accuracy of their first period guess and (a): the error in the first period decision, and (b): the likelihood of switching to the source's estimate. Results are shown pooling treatment conditions in each experiment.

ure A.4 shows that the correlation is virtually zero when the quality signal is provided. Strikingly, the increase in switching when beliefs about the success of a particular caste group moves from 50% to 90% is approximately the same as the difference induced by experimentally varying the signal quality by the same amount. As these beliefs are elicited after the main tasks, these results cannot be given a causal interpretation.

Summary. These results show that (i) beliefs about the quality of information causally influence learning, (ii) learning rates are low, even when information quality is high, (iii) the trade-off between information quality and subjective confidence is an important mechanism that moderates learning. At the same time, participants over-estimate others' performance on the experimental task, and believe that performance differs by religion and caste. Thus, while using identity to proxy for information quality could be misleading, the provision of the quality signal eliminates the role of underlying beliefs. Additional analyses (presented in Appendix C.5) reveal that switching is higher when a quality signal is provided than when it is not.

4 The Role Of Preferences

This section focuses on causally identifying preferences for the identity of the information source. The analysis begins with the average treatment effects in the four experiments, before moving on to in-group preferences in the *Caste* and *Religion* experiments, and concludes with an exploration of different sources of preference heterogeneity.

Figure 5: Beliefs about the performance of different groups

(a) Caste: High vs. low status

(b) Religion: Hindus vs. Muslims
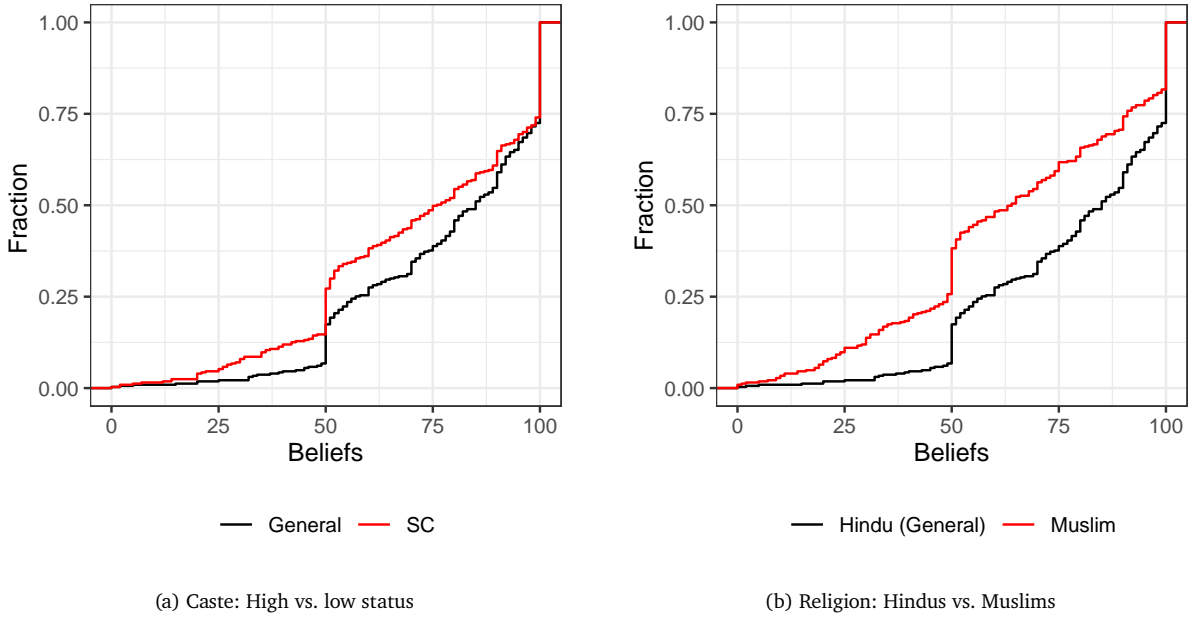
Notes. Cumulative frequencies of participant's beliefs about the likelihood that a person from a particular caste category or religion makes an accurate first-period estimate in the task. Panel (a) – Red line: O category Hindu, Black line: G category Hindu. Panel (b) – Red line: Muslim, Black line: G category Hindu.

4.1 Preferences for the identity of information sources

I estimate the following specification using OLS regressions to causally identify preferences for the identity of information sources:

$$Switch_{i,n} = \beta_0 + \beta_1 T_i + Q_{i,n} + \gamma_i + \nu_n + \epsilon_i, \tag{1}$$

where *Switch* is an indicator variable for participant i in task n. *Switch* $= 1$ if the participant switches to the source in the second period and 0 otherwise. T_i is an indicator for the treatment group that participants are randomly assigned to: $T_i = 1$ if the participant is assigned to see a source belonging to the General Caste (in *Caste*), is a Hindu (*Religion*), from their In-group (*Minimal*), or a Computer (*Human vs. Computer*). $Q_{i,n}$ is the level of the quality signal seen by participant i in task n. γ_i is a set of demographic controls (age, gender, tertiary education, and employment status), and i's confidence in the accuracy of their first-period decision. ν_n is a vector of task-specific controls: the order, specific task, and whether the shown decision is correct. Standard errors are heteroscedasticity-robust, clustered at the participant level. The coefficient of interest is β_1, which identifies preferences for learning from one identity group over another.

Hypothesis 1. *The estimate of $\beta_1 \neq 0$ in each of the experiments, indicating that participants prefer to learn more from one of the two identity groups: (i) a General caste or SC/ST/OBC caste, (ii) a Hindu or a Muslim, (iii) experimentally assigned in-group or out-group, (iv) a Computer or an anonymous human.*

Table 2: Regression analysis: Preferences for the identity of information sources.

	Dep. var.: Switch to source			
	Caste	Religion	Minimal	Computer
	(i)	(ii)	(iii)	(iv)
General Caste Source	-0.033			
	(0.021)			
Hindu Source		-0.006		
		(0.019)		
In-group Source			-0.010	
			(0.027)	
Computer Source				0.156***
				(0.021)
General Caste	-0.015			
	(0.022)			
Hindu		-0.042*		
		(0.023)		
Quality	0.140***	0.127***	0.614***	0.642***
	(0.038)	(0.045)	(0.092)	(0.063)
Constant	0.431***	0.410***	0.241**	0.212***
	(0.072)	(0.072)	(0.101)	(0.071)
Task controls	✓	✓	✓	✓
Demog. controls	✓	✓	✓	✓
R^2	0.035	0.027	0.113	0.134
Dependent variable mean	0.320	0.236	0.312	0.365
Observations	4,952	5,063	1,629	3,473
Individuals	851	853	278	593

Notes. Average treatment effects in the different experiments, estimates from OLS regressions of Equation 1. The dependent variable is whether a participant switches in the second period. Controls are task and order fixed effects, whether the source is correct, and demographic characteristics (the participant's age and dummies for employment, college education and gender). Robust standard errors, clustered at the participant level. $* p < 0.10, ** p < 0.05, *** p < 0.01$.

Table 2 presents the results from estimating this equation separately for each of the four main experiments. The estimated average treatment effect in the *Caste*, *Religion*, and *Minimal* experiments is statistically indistinguishable from zero, and the 95% confidence intervals are within 0.1 standard deviations. There is no evidence to support Hypothesis 1 (i)-(iii) that participants have preferences for whether the source is a *G* caste or *O* caste group individual in the *Caste* experiment, a Hindu or a Muslim in the *Religion* experiment, or their experimentally assigned in-group member or an out-group member in the *Minimal* experiment.

In contrast, the estimated treatment effect is positive and statistically significant for the *Human vs. Computer* experiment. The magnitude of the effect ($\approx$ 15% points) is quantitatively large, about a third of the fraction switching in the *Human* condition. The results support Hypothesis 1 (iv) – participants prefer to switch more to decisions made by a computer or algorithm than by another

human.[10] This also supports "algorithmic appreciation", that humans prefer to learn from non-social sources when the quality of information is precisely known.

These results are robust to the inclusion of different sets of controls and background characteristics. Detailed regression analyses – presented in Appendix Tables B.3–B.6 – show that the estimated average treatment effects are not affected by the choice of control variables.

Ruling out noisiness or inattention

Figure 6 shows the results from a battery of robustness tests exploring whether the results are driven by a lack of comprehension of the task, confusion, or inattention. These tests use features of participant's decisions that could represent random decision making, cognitive fatigue, or a lack of understanding of the task and incentive structure. The panels show estimates of the average treatment effect for each experiment under different sample restrictions using the specification in Equation 1.

First, participants may be more motivated, energetic, or likely to remember instructions at the beginning of the experiment. Restricting the sample to the first two (of six) tasks does not affect the estimated treatment effect relative to the full sample. Next, completing tasks very quickly or very slowly may reflect inattention or distraction. The third and fourth estimates in each panel exclude decisions that are in the top and bottom 10% of time taken while making the switching decision. Excluding such decisions has virtually no effect on the estimates. Next, participants who never switch may arguably do so because they just want to get through the tasks quickly. Restricting the sample to participants who switch at least once, the estimates are very similar in three of the four experiments. The estimate is statistically significant (and negative) at the 5% level in the *Caste* experiment.

Finally, experiment *Caste* included a design feature to specifically examine participant inattention. The last of the six tasks faced by a participant was the same as one of the first 3 tasks. The correlation between participants' responses on the identical tasks is 0.62, which is quite strong. Further, the estimated treatment effect on a restricted subsample of participants whose decisions on identical tasks differ by less than 10 – an indicator of high consistency – is very similar to the estimate using the full sample.

Taken together, the consistency of the results across all of these robustness tests support the main results that participants do not have a preference for the identity of the information source, and that they have a preference for information from non-social sources over information from another human.

4.2   In-group preferences and overlapping identities

A person's identity *relative* to the source of information could influence switching in the experiment, given previous research showing that identities affect decision-making through in-group favouritism and out-group parochialism (Shayo, 2020; Charness and Chen, 2020). While the *Minimal* experiment finds no evidence of in-group preferences with experimentally assigned identities, the *Religion* and *Caste* experiments allow for further investigation with naturally-occurring identities. Participants in

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[10]Column (v) and (vi) of Appendix Table B.6 shows that the results with and without including decisions from the *Minimal* experiment in the Human treatment for this experiment are virtually the same.

Figure 6: Robustness tests

(a) Caste

(b) Religion

(c) Minimal Identity

(d) Human vs. Computer
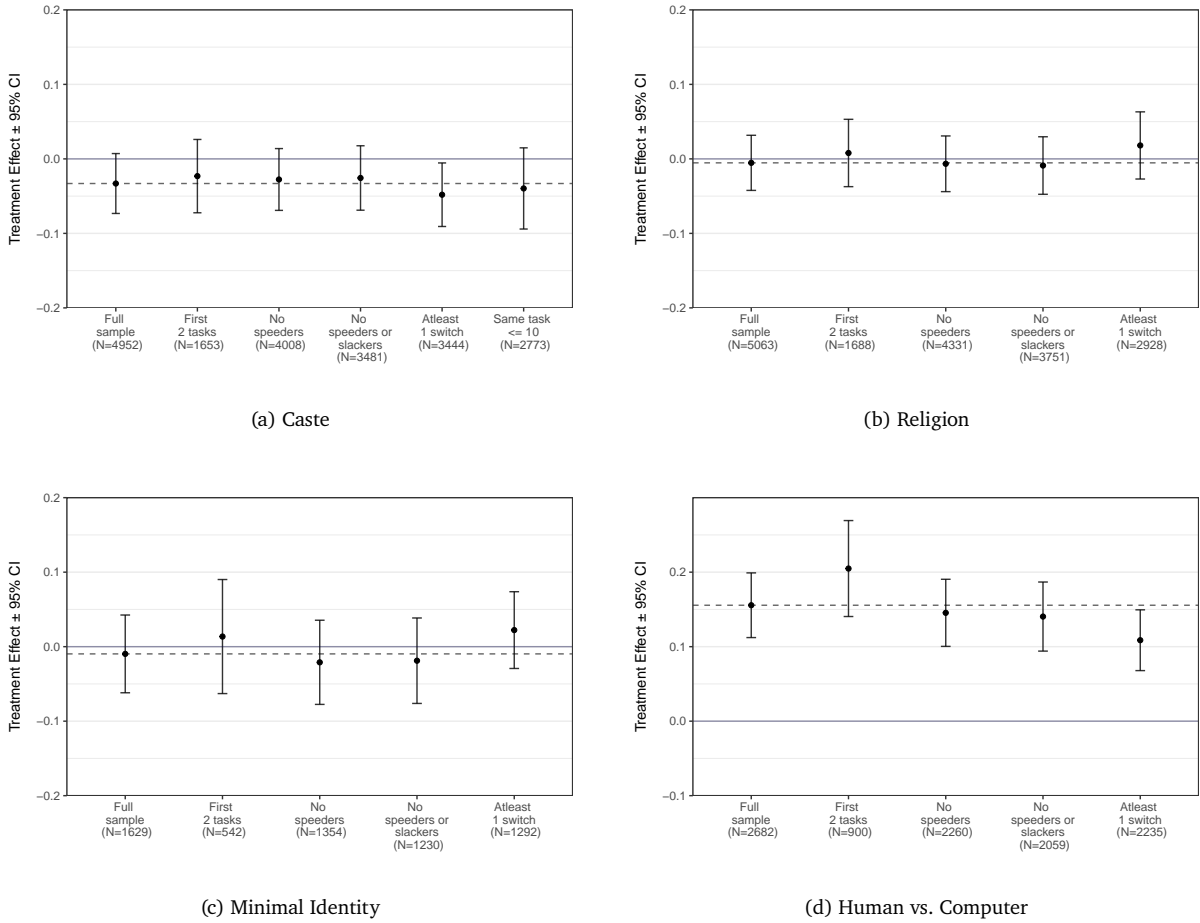
Notes. Each point is the estimated coefficient on the treatment dummy variable from OLS regressions of Equation 1 under different sample restrictions. Error bars indicate 95% confidence intervals. Standard errors are clustered at the participant level. Controls are: A set of demographic controls, task and order fixed effects, confidence, whether the source was correct, and the quality of the information source. The dashed lines are a reference for the point estimate of the average treatment effect using the main estimation sample.

these experiments self-report their caste group and religion, enabling an analysis of whether they prefer information from an in-group source (same caste or religion) over an out-group source (different caste or religion).

I estimate the following specification using OLS regressions to identify the existence of in-group preferences for the identity of the information source:

$$Switch_{i,n} = \beta_0 + \beta_1 T_i + \beta_2 I_i + \beta_3 T_i \times I_i + Q_{i,n} + \gamma_i + \mu_n + \epsilon_i, \tag{2}$$

where I_i is an indicator variable of the participant's identity: In experiment *Caste*, $I_i = 1$ if the participant belongs to the general category (G) and $I_i = 0$ if the participant belongs to the SC/ST/OBC categories. In experiment *Religion*, $I_i = 1$ if the participant is Hindu and $I_i = 0$ if the participant is Muslim. The sample for the *Religion* experiment is restricted to Hindu and Muslim participants to

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allow for the construction of clear in-groups.

The coefficient β_1 is the treatment effect of seeing a $T_i = 1$ source relative to a $T_i = 0$ source for $I_i = 0$ participants. $\beta_1 + \beta_3$ is the treatment effect of seeing a $T_i = 1$ source relative to a $T_i = 0$ source for $I_i = 1$ group participants. The interaction coefficient β_3 is the difference in the treatment effects between $I_i = 0$ and $I_i = 1$ identity group participants.

Hypothesis 2. *The estimate of $\beta_3 \neq 0$, indicating that participants learn differently from an in-group source than from an out-group source within the Religion and Caste experiments.*

Columns (i)-(ii) of Table 3 present the results from estimating equation 2 in the *Caste* and *Religion* experiment samples. The estimated coefficients on the interaction terms are not (individually or jointly) statistically significant. The results are robust to the inclusion of task and demographic controls, and to controlling for participant's stated confidence. Appendix Tables B.7 and B.8 present the results from same robustness tests and show that the results are largely consistent. Further, there is no evidence that participants belonging to different castes or religions switch differently, nor are the treatment effects for any of the subgroups statistically significant. Taken together, there is no evidence that participants belonging to different castes or religions have in-group preferences for information from their caste or religion in-groups.

Overlapping identities. The analysis so far has focused on a single dimension of identity. However, in naturally occurring contexts, people possess multiple identities which may affect learning in different ways. In the Indian context, people have both religious and caste identities. The importance of caste identity and the associated behavioural norms and prescriptions vary between caste groups and across religions. The *Religion* experiment includes participants of different religions who also hold caste identities, which makes it possible to investigate how preferences for the religious identity of sources vary across different overlaps of religious and caste identities.

I estimate the following specification to study the effect of overlapping religious and caste identities in the *Religion* experiment:

$$Switch_{i,n} = \beta_0 + \beta_1 T_i + \beta_2 C_i + \beta_3 T_i \times C_i + Q_{i,n} + \gamma_i + \mu_n + \epsilon_i, \tag{3}$$

where C_i is the caste identity of participant i. $C_i = 0$ if the participant belongs to the SC/ST/OBC caste category, and $C_i = 1$ if the participant belongs to the general caste category.

Columns (iii)-(iv) of Table 3 present estimates of Equation 3 using sub-samples of Hindu and Muslim participants within experiment *Religion*. Column (iii) shows that Hindu participants belonging to the SC/ST/OBC castes switch less when they see a Hindu source than when they see a Muslim source. The interaction term (Hindu Source x General Caste) is positive and statistically significant, indicating that General caste participants switch more to Hindu sources than Muslim sources when compared to SC/ST/OBC participants. Turning to the Muslim sub-sample (Column (iv)), there is no evidence that switching to Hindu or Muslim sources differs by the participant's caste group.

These heterogeneity results suggest that preferences for the identity of information sources may exist for (or between) specific identity groups. The analysis also highlights a key challenge for re-

Table 3: Regression analysis: Heterogeneous effects by caste category

	Dep. var.: Switch to source			
	In-group Preferences Experiment		Overlapping Identities Participant Religion	
	Caste	Religion	Hindu	Muslim
	(i)	(ii)	(iii)	(iv)
General Caste Source	-0.013			
	(0.035)			
General Caste Source × General Caste	-0.032			
	(0.043)			
Hindu Source		0.079	-0.105***	0.073
		(0.065)	(0.038)	(0.091)
Hindu Source × Hindu		-0.093		
		(0.068)		
Hindu Source × General Caste			0.141***	-0.005
			(0.046)	(0.128)
General Caste	0.000		-0.102***	0.009
	(0.031)		(0.035)	(0.077)
Hindu		0.003		
		(0.041)		
Quality	0.056***	0.091*	0.100**	0.054
	(0.015)	(0.049)	(0.051)	(0.164)
Constant	0.490***	0.372***	0.420***	0.321
	(0.068)	(0.085)	(0.085)	(0.240)
Task controls	✓	✓	✓	✓
Demog. controls	✓	✓	✓	✓
R^2	0.035	0.024	0.029	0.067
Dependent variable mean	0.320	0.230	0.225	0.270
Observations	4,952	4,348	3,841	507
Individuals	851	733	647	86

Notes. Columns (i)–(ii): Estimates of Equation 2 for in-group preferences in the *Caste* and *Religion* experiments. Columns (iii)–(iv): Estimates of Equation 3 for in-group preferences with overlapping identities using sub-samples of Hindu and Muslim participants in the *Religion* experiment. The dependent variable is 1 if the participant switches to the source's decision y_s. Demographic controls are the participant's age and dummies for employment, college education and gender. Task controls include task and order effects, and an indicator for whether the source is correct. Standard errors are clustered at the participant level. $* p < 0.10, ** p < 0.05, *** p < 0.01$.

search with naturally-occurring identities, that individuals belong to many identity groups concurrently which may have complex interactions.

4.3   Heterogeneity

Behavioural mechanisms

The balls-and-urns setup enables an investigation of several mechanisms using both exogenously manipulated experiment parameters and endogenous behavioural responses. The mechanisms ex-

amined are: (i) experimental variation in the quality of the information (whether responsiveness to quality varies by source identity), (ii) experimental variation in whether the source is correct or incorrect (whether participants discern incorrect sources differently based on identity), (iii) the participant's confidence in their first-period decision (whether the quality-confidence trade-off varies by identity), (iv) the accuracy of the participant's first-period decision (whether high or low ability participants react differently to source identity), (v) the difference between the first-period decision and the source's decision ($|y_1 - y_S|$, whether responses to more or less disconfirming sources differs by identity), and (vi) the time spent when making the switching decision (whether more deliberative decisions differ by source identity). Conceptually, evidence that these mechanisms affect behaviour based on the source's identity would support the existence of identity preferences that emerge based on contextual features or deliberation when making these decisions.

As a benchmark, these mechanisms affect how participants switch in all experiments, independent of identity – participants switch more when they see sources that are of higher quality, when sources provide the correct answer, when they are less confident in their first-period decision, when their first-period decision is incorrect, when there is a larger distance between the source's and their own decision, and when they spend more time on the switching decision. These observations are largely consistent with the literature studying balls-and-urns tasks (reviewed in Benjamin (2019)). Interestingly, participants are more likely to switch when the source more strongly disconfirms their first-period decision (i.e. participants are more likely to switch in the face of "bad news").

I estimate the following specification using OLS to explore the interaction between a mechanism and the source's identity:

$$Switch_{i,n} = \beta_0 + \beta_1 T_i + \beta_2 M_{i,n} + \beta_3 T_i \times M_{i,n} + \gamma_i + \mu_n + \epsilon_i, \tag{4}$$

where $M_{i,n}$ denotes whether participant i encounters mechanism M in task n. The coefficient on the interaction term β_3 can be interpreted as the difference in switching associated with the mechanism because of a difference in the source's identity. Appendix Tables B.9, B.10, B.11, and B.12 present the results from estimating this specification for each of the 6 mechanisms within each experiment.

Across experiments, the results provide very little evidence that these mechanisms interact with identity, with only 3 of the 24 estimated coefficients being statistically significant at the 5% level. In the *Religion* experiment, the results in Column (i) of Table B.10 show that participants may respond more to an increase in the quality of a Hindu source than a Muslim source.[11] In the *Human vs. Computer experiment*, the results in columns (v) and (vi) of Table B.12 show that participants may switch less to a computer than to another human when (i) the distance between the source decision and the participant's first-period decision increases, and (ii) when they spend more time on the switching decision.

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[11]An analysis of this effect (not reported) shows that the difference in responsiveness to the quality of information appears to be driven by General category Hindus. SC/ST/OBC Hindus and Muslims of all caste groups do not appear to be differentially sensitive based on the source's religion.

Strength of caste identity

How strongly people identify with (or value) their caste identity may lead to heterogeneity in preferences for the (caste) identity of information sources. To explore this, I elicited (i) the caste and religious composition of participants' friend networks, and (ii) their support for caste-based affirmative action (commonly known as "reservations", an important topic in the Indian context). Arguably, people who are less exposed to people from other castes or religions may have preferences for information from their in-groups than from their out-groups. Similarly, people who do or do not support caste-based affirmative action policies may identify differently with their caste identity.

Appendix Figure A.5 shows the estimated coefficients of the difference in the average treatment effect between people who have fewer friends from other castes, fewer friends from other religions, or are against caste-based affirmative action policies, relative to those who have more friends from other castes/religions or who support affirmative action policies.[12] None of the estimated coefficients are statistically significant.

Taken together, while the findings of these heterogeneity analyses raise some interesting questions for future research, the lack of heterogeneous effects provides strong support for the main results.

5   Conclusion

This paper studies how the identity of an information source affects whether people choose to learn, using online experiments that study both naturally occurring and experimentally assigned identities. The results show that while beliefs about information quality influence learning significantly, preferences for the identity of the information source do not play a role when the source is human. The results from the *Human v. Computer* experiment indicate that people prefer to learn from a non-social source than from another human, and present an interesting research question to identify the mechanisms underlying this effect both theoretically and empirically.

The experimental design examines a novel form of learning where a rational benchmark predicts that no learning will occur. It provides evidence of an under-studied source of learning in situations where stakeholders and sources have access to the same information but may differ in how they interpret it. This channel is also likely to influence learning in situations where both private and public information are available. Characterising how learning is motivated by a quest for new information and for better interpretations of the same information presents an exciting research agenda, closely related to the growing literature on the role of narratives in economic decision-making (Shiller, 2017; Graeber et al., 2022; Barron and Fries, 2023).

The experiment developed in this paper is deliberately abstract, which helps eliminate the numerous channels through which identity or contextual factors could influence learning. While this approach enables preference identification, it does so in a stylised setting where there is no possibility of prolonged association with out-group members. On the other hand, the experiment design shares

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[12]The estimated specification is $Switch_{i,n} = \beta_0 + \beta_1 In_i + \beta_2 E_i + \beta_3 In_i \times E_i + Q_{i,n} + \gamma_i + \mu_n + \epsilon_i$, where $In_i = 1$ if the participant and the source are in the same caste group and E_i is an indicator variable for each mechanism.

core elements with many everyday decisions – we read newspaper articles, read online reviews, or watch news on the TV which may be delivered by people from different social groups. Future research can adapt the experiment introduced in this paper to study how identity influences social learning in situations involving repeated interactions and more natural decision-making environments.

These results carry important implications for policy-makers and organisations. Although the results show that preferences for identity do not matter, this holds only when the quality of information is both salient and precise. As providing an unambiguously clear signal is difficult in most real-world situations, policy-makers would benefit from finding ways to minimise the role of messenger identity when designing information delivery campaigns and outreach efforts. Emphasising information quality and delivering information through non-social channels may yield better results in settings such as the take-up of social welfare programs, adoption of better health practices, or engineering changes in harmful social norms.

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APPENDIX

A   Additional Figures

Figure A.1: Distribution of switching decisions – participant level
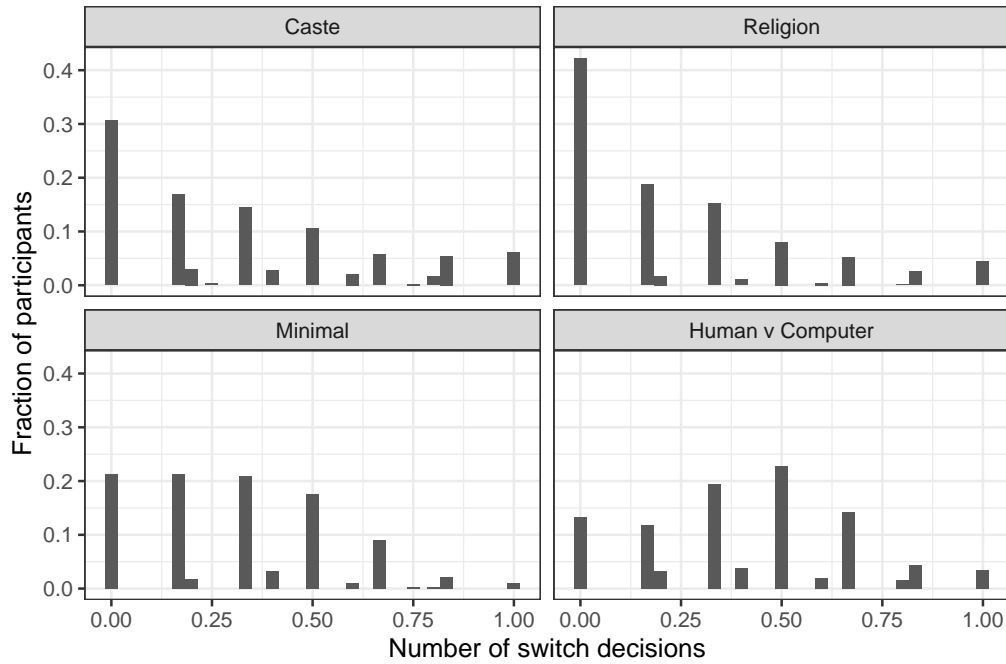
Notes. The graph shows the participant-wise distribution of the fraction of second-period decisions in which they choose to switch to the source. Note that in some cases the fraction is not a multiple of 1/6 as some decisions are excluded (as stated in Section 3.4).

Figure A.2: Effect of beliefs about information quality on learning (controlling for differences between treatments)
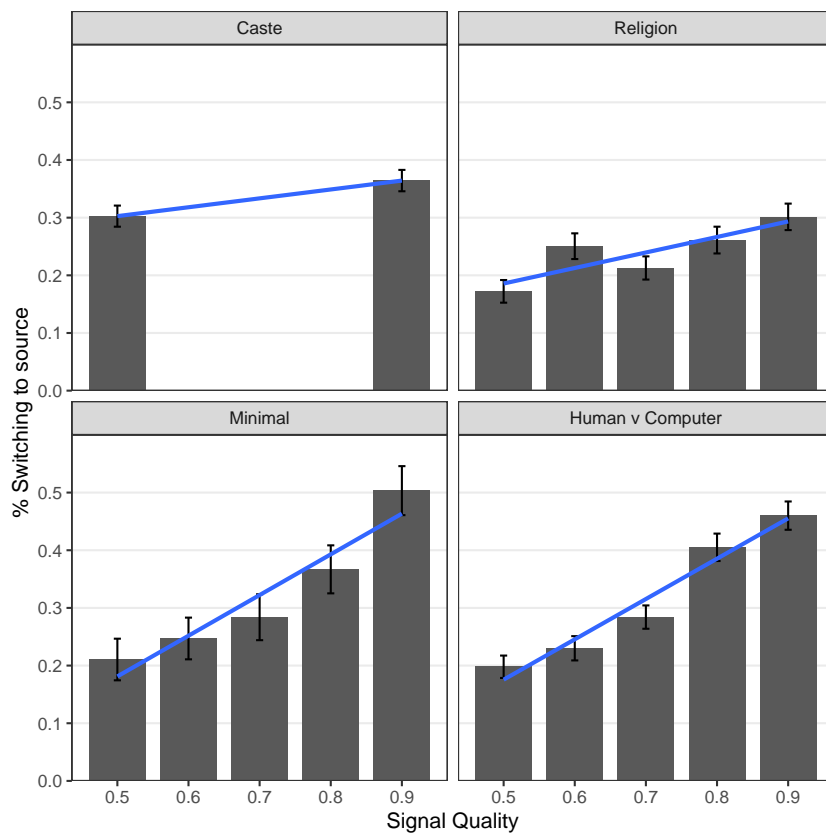
Notes. The graph shows the fraction of decisions where participants choose to switch to the source in each experiment, at each level of source quality Q, controlling for the treatment to which participants are assigned to. $Q \in \{50, 90\}$ in *Caste*, and $Q \in \{50, 60, 70, 80, 90\}$ in the other experiments. Error bars indicate 95% confidence intervals.

Figure A.3: Confidence vs. quality: Switching patterns
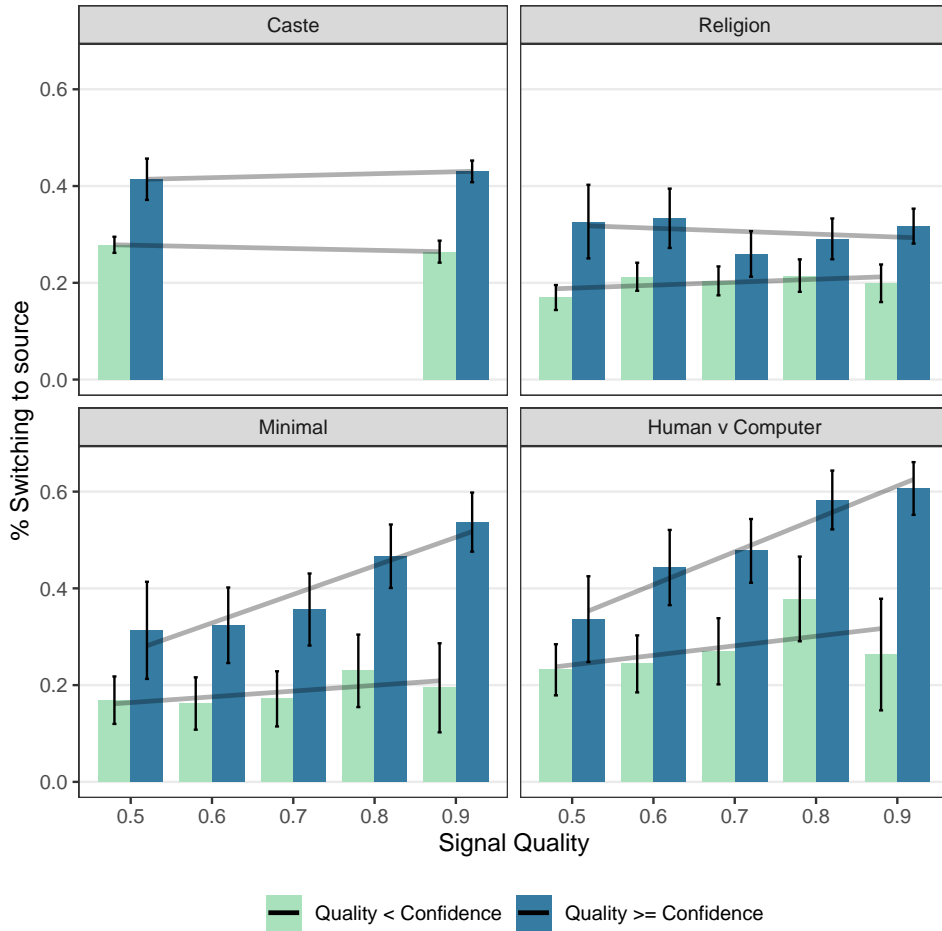
Notes. The graph shows the fraction of decisions where participants choose to switch to the source by the quality of the source. The light coloured bars are decisions when source quality is lower than participants' confidence in their first-period decision, dark coloured bars are decisions where quality is higher than confidence. Error bars indicate 95% confidence intervals.

Figure A.4: Role of underlying beliefs

(a) Quality of information is unknown

(b) Quality of information is known
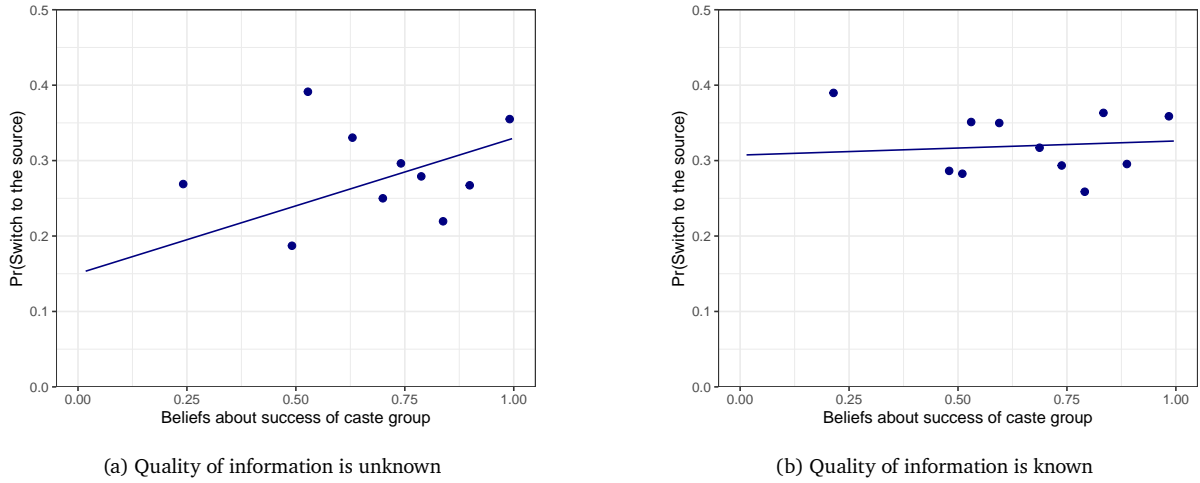
Notes. Binned scatter plots of participants' likelihood of switching to a source (with an experimentally assigned caste identity) against incentivised beliefs about the likelihood that a random individual of that caste is likely to make a correct decision on the task. (a): *Caste - No Signal*, participants are not informed about the quality of the source. (b): *Caste*, participants are given the quality signal.

Figure A.5: Mechanisms: *Caste* Experiment
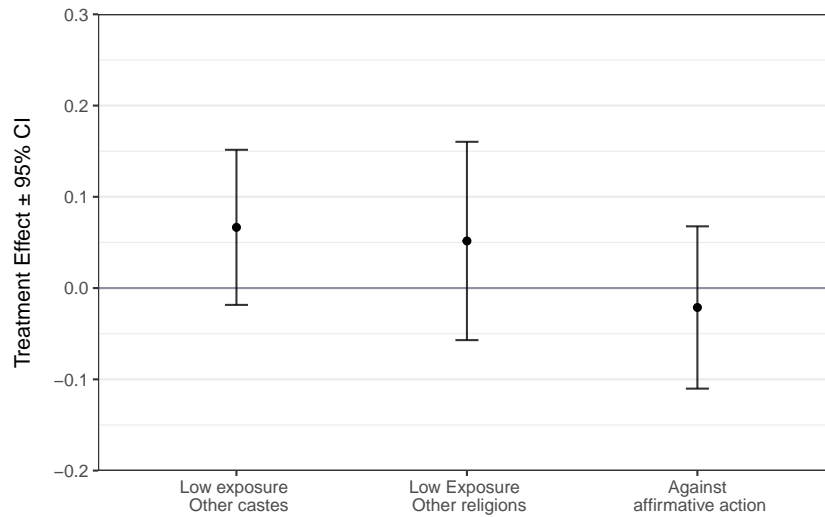
Notes. Results from regressions of whether participants switch on an indicator of whether participants see an in-group source, an indicator of caste identity strength, and their interaction, on switching. The figure show the estimated coefficients of the interaction term of whether participants see an in-group source and an indicator for (i) low exposure to people from other castes, (ii) low exposure to people from other religions, and (iii) whether they oppose caste-based affirmative action policies. in the *Caste* experiment. Standard errors are clustered at the participant level in all regressions.

B Additional Tables

Table B.1: List of balls and urns tasks

#	Base Rate (p)	Red Balls (θ)	Total (Red) Draws	True Value (y_T)	Correct	Incorrect
1	0.7	70	3 (1)	50	51	25
2	0.7	70	5 (2)	50	48	26
3	0.9	70	3 (2)	95.5	95	76
4	0.9	90	3 (0)	1.2	3	23
5	0.9	70	5 (4)	99.1	97	82
6	0.5	70	5 (4)	92.7	92	77

Notes. Base rate is the probability with which the red bag is selected. *Red balls* is the number of red balls in the red bag. *Total (red) draws* is the number of balls that are drawn from the selected bag, with the number of red balls drawn in brackets. *True value* is the Bayesian posterior probability that the red bag was selected. *Correct* and *Incorrect* values for the source in each task are selected from responses on the same tasks in a previous study using the procedure described in Section 2.

Table B.2: Sample Descriptives

	Caste	Religion	Minimal	Human v Computer
Age	32	31	32	32
% Men	52	60	60	55
% College	90	89	77	75
% Employed	84	83	68	72
Decision Time	25	20	17	18
Participants	851	853	278	315
Decisions	5106	5118	1668	1890

Notes. Sample descriptives for the experiments presented in the paper. College and Employment are indicator variables = 1 if the participant has tertiary education or is not unemployed. Decision time is the average time (in seconds) taken by participants in the second period.

Table B.3: Regression analysis: Average treatment effects – Caste

| | | | Dep. var.: Switch to source | | | |
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
General Caste Source	-0.028	-0.029	-0.028	-0.028	-0.027	-0.033
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Source is wrong			-0.041***	-0.041***	-0.015	-0.012
			(0.015)	(0.015)	(0.017)	(0.016)
General Caste				-0.015	-0.014	-0.015
				(0.022)	(0.022)	(0.022)
Quality					0.134***	0.140***
					(0.039)	(0.038)
Confidence						-0.003***
						(0.000)
Constant	0.334***	0.313***	0.325***	0.328***	0.227***	0.431***
	(0.015)	(0.023)	(0.060)	(0.060)	(0.068)	(0.072)
Task controls		✓	✓	✓	✓	✓
Demog. controls			✓	✓	✓	✓
R^2	0.001	0.003	0.008	0.009	0.011	0.035
Dependent variable mean	0.320	0.320	0.320	0.320	0.320	0.320
Observations	4,952	4,952	4,952	4,952	4,952	4,952
Individuals	851	851	851	851	851	851

Notes. Average treatment effects in experiment *Caste*, estimates from OLS regressions of Equation 1. Controls are task and order fixed effects, whether the source is correct, and demographic characteristics (the participant's age and dummies for employment, college education and gender). Robust standard errors, clustered at the participant level. $* p < 0.10, ** p < 0.05, *** p < 0.01$.

Table B.4: Regression analysis: Average treatment effects – Religion

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
			Dep. var.: Switch to source			
Hindu Source	-0.010	-0.010	-0.008	-0.007	-0.007	-0.006
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Source is wrong			-0.050***	-0.050***	-0.039***	-0.038***
			(0.013)	(0.013)	(0.014)	(0.014)
Hindu				-0.045*	-0.046*	-0.042*
				(0.023)	(0.023)	(0.023)
Quality					0.130***	0.127***
					(0.046)	(0.045)
Confidence						-0.002***
						(0.000)
Constant	0.241***	0.228***	0.314***	0.341***	0.246***	0.410***
	(0.014)	(0.020)	(0.054)	(0.056)	(0.066)	(0.072)
Task controls		✓	✓	✓	✓	✓
Demog. controls			✓	✓	✓	✓
R^2	0.000	0.003	0.008	0.010	0.012	0.027
Dependent variable mean	0.236	0.236	0.236	0.236	0.236	0.236
Observations	5,063	5,063	5,063	5,063	5,063	5,063
Individuals	853	853	853	853	853	853

Notes. Average treatment effects in experiment *Religion*, estimates from OLS regressions of Equation 1. Controls are task and order fixed effects, whether the source is correct, and demographic characteristics (the participant's age and dummies for employment, college education and gender). Robust standard errors, clustered at the participant level. $* p < 0.10, ** p < 0.05, *** p < 0.01$.

Table B.5: Regression analysis: Average treatment effects – Minimal identity

| | | | Dep. var.: Switch to source | | |
	(i)	(ii)	(iii)	(iv)	(v)
In-group Source	-0.018	-0.018	-0.025	-0.030	-0.010
	(0.028)	(0.029)	(0.028)	(0.029)	(0.027)
Source is wrong			-0.110***	-0.049*	-0.049*
			(0.025)	(0.026)	(0.026)
Quality				0.606***	0.614***
				(0.092)	(0.092)
Confidence					-0.005***
					(0.001)
Constant	0.321***	0.361***	0.487***	0.047	0.241**
	(0.019)	(0.039)	(0.079)	(0.105)	(0.101)
Task controls		✓	✓	✓	✓
Demog. controls			✓	✓	✓
R^2	0.000	0.005	0.023	0.052	0.113
Dependent variable mean	0.312	0.312	0.312	0.312	0.312
Observations	1,629	1,629	1,629	1,629	1,629
Individuals	278	278	278	278	278

Notes. Average treatment effects in experiment *Minimal*, estimates from OLS regressions of Equation 1. Controls are task and order fixed effects, whether the source is correct, and demographic characteristics (the participant's age and dummies for employment, college education and gender). Robust standard errors, clustered at the participant level. $* \, p < 0.10, ** \, p < 0.05, *** \, p < 0.01$.

Table B.6: Regression analysis: Average treatment effects – Human vs. Computer

	Dep. var.: Switch to source					Excluding *Minimal*
	Pooling *Minimal*					
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Computer Source	0.173***	0.173***	0.174***	0.176***	0.156***	0.151***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.021)	(0.025)
Source is wrong			-0.121***	-0.058***	-0.061***	-0.074***
			(0.017)	(0.018)	(0.018)	(0.024)
Quality				0.651***	0.642***	0.668***
				(0.064)	(0.063)	(0.088)
Confidence					-0.005***	-0.005***
					(0.000)	(0.000)
Constant	0.317***	0.376***	0.479***	0.002	0.212***	0.203**
	(0.012)	(0.026)	(0.056)	(0.073)	(0.071)	(0.101)
Task controls		✓	✓	✓	✓	✓
Demog. controls			✓	✓	✓	✓
R^2	0.026	0.032	0.047	0.079	0.134	0.142
Dependent variable mean	0.365	0.365	0.365	0.365	0.365	0.412
Observations	3,473	3,473	3,473	3,473	3,473	1,844
Individuals	593	593	593	593	593	315

Notes. Average treatment effects in experiment *Human vs. Computer*, estimates from OLS regressions of Equation 1. Controls are task and order fixed effects, whether the source is correct, and demographic characteristics (the participant's age and dummies for employment, college education and gender). Robust standard errors, clustered at the participant level. $* p < 0.10, ** p < 0.05, *** p < 0.01$.

Table B.7: Robustness – In-group preferences, *Caste* experiment

	Dep. var.: Switch to source					
	Full sample (i)	First 2 tasks (ii)	No Speeders (iii)	No speeders or slackers (iv)	Atleast 1 switch (v)	Same Task <= 10 (vi)
General Caste Source	-0.013	0.021	-0.011	-0.012	-0.024	-0.020
	(0.035)	(0.042)	(0.035)	(0.039)	(0.036)	(0.051)
General Caste	0.000	0.007	-0.009	-0.028	-0.009	0.015
	(0.031)	(0.036)	(0.032)	(0.035)	(0.033)	(0.049)
General Caste Source × General Caste	-0.032	-0.069	-0.025	-0.016	-0.037	0.004
	(0.043)	(0.053)	(0.044)	(0.048)	(0.045)	(0.067)
Quality	0.056***	0.063**	0.068***	0.062***	0.152***	0.127**
	(0.015)	(0.026)	(0.017)	(0.020)	(0.050)	(0.059)
Constant	0.490***	0.500***	0.484***	0.546***	0.559***	0.508***
	(0.068)	(0.084)	(0.072)	(0.082)	(0.081)	(0.116)
Task controls	✓	✓	✓	✓	✓	✓
Demog. controls	✓	✓	✓	✓	✓	✓
R^2	0.035	0.051	0.039	0.042	0.029	0.043
Dependent variable mean	0.320	0.324	0.325	0.311	0.460	0.291
Observations	4,952	1,653	4,008	3,053	3,444	2,055
Individuals	851	851	842	825	590	354

Notes. OLS estimates of Equation 2 for the robustness analysis of in-group preferences in the Caste experiment. Controls are task and order fixed effects, and demographic characteristics(the participant's age and dummies for employment, college education and gender). Standard errors are clustered at the participant level. $* p < 0.10, ** p < 0.05, ***p < 0.01$.

Table B.8: Robustness – In-group preferences, *Religion* experiment

	Full sample (i)	First 2 tasks (ii)	No Speeders (iii)	No speeders or slackers (iv)	Atleast 1 switch (v)
	Dep. var.: Switch to source				
Hindu Source	0.079	0.027	0.077	0.071	0.157**
	(0.065)	(0.081)	(0.068)	(0.073)	(0.075)
Hindu Source × Hindu	-0.093	-0.013	-0.090	-0.079	-0.159**
	(0.068)	(0.085)	(0.071)	(0.077)	(0.080)
Hindu	0.003	-0.025	-0.001	0.000	0.053
	(0.041)	(0.054)	(0.043)	(0.047)	(0.049)
Quality	0.091*	0.103	0.139***	0.136**	0.174**
	(0.049)	(0.079)	(0.052)	(0.059)	(0.077)
Constant	0.372***	0.409***	0.370***	0.403***	0.332***
	(0.085)	(0.116)	(0.088)	(0.096)	(0.111)
Task controls	✓	✓	✓	✓	✓
Demog. controls	✓	✓	✓	✓	✓
R^2	0.024	0.020	0.029	0.035	0.025
Dependent variable mean	0.230	0.231	0.236	0.225	0.407
Observations	4,348	1,449	3,698	2,873	2,458
Individuals	733	733	732	724	414

Notes. OLS estimates of Equation 2 for the robustness analysis of in-group preferences in the Religion experiment. Controls are task and order fixed effects, and demographic characteristics(the participant's age and dummies for employment, college education and gender). Standard errors are clustered at the participant level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table B.9: Regression analysis: Mechanisms in the Caste experiment

	Dep. var.: Switch to source					
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
General Caste Source	-0.028	-0.036	0.014	-0.024	-0.025	-0.031
	(0.053)	(0.022)	(0.069)	(0.021)	(0.025)	(0.022)
General Caste Source × Quality	-0.007					
	(0.071)					
General Caste Source × Source is wrong		0.010				
		(0.030)				
General Caste Source × Confidence			0.001			
			(0.001)			
General Caste Source × Guess 1 correct				-0.061*		
				(0.037)		
General Caste Source × Dist. to Source					0.000	
					(0.001)	
General Caste Source × Decision time (z)						0.008
						(0.017)
Quality	0.144***	0.141***	0.145***	0.142***	0.142***	0.148***
	(0.054)	(0.038)	(0.039)	(0.038)	(0.038)	(0.040)
Source is wrong	-0.012	-0.016	-0.010	-0.008	-0.011	-0.007
	(0.016)	(0.022)	(0.016)	(0.016)	(0.016)	(0.017)
Confidence	-0.003***	-0.003***	-0.004***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Guess 1 correct				-0.071**		
				(0.029)		
Dist. to Source					0.000	
					(0.000)	
Decision time (z)						0.021
						(0.014)
Constant	0.424***	0.428***	0.426***	0.414***	0.406***	0.447***
	(0.076)	(0.071)	(0.081)	(0.071)	(0.073)	(0.077)
Task controls	✓	✓	✓	✓	✓	✓
Demog. controls	✓	✓	✓	✓	✓	✓
R^2	0.035	0.035	0.039	0.040	0.035	0.038
Dependent variable mean	0.320	0.320	0.320	0.320	0.320	0.312
Observations	4,952	4,952	4,907	4,952	4,952	4,346
Individuals	851	851	850	851	851	843

Notes. The table presents estimates from OLS regressions of switching on the treatment indicator interacted with one of six mechanism variables within the *Caste* experiment, controlling for demographics, task parameters, and task order. Demographic controls are the participant's age and dummies for employment, college education and gender. Standard errors are clustered at the participant level. *Quality* is a continuous variable ranging from 0.5 to 0.9. *Source is wrong* =1 if the shown source's estimate is incorrect. Confidence is a participant's confidence in the accuracy of their independent estimate (0 to 100). *Guess 1 correct* = 1 if the participant made a correct first period estimate. *Dist. to source* $= |y_s - y_1|$. *Decision time* is the z-standardised time in seconds taken by participant on the page where they decide whether to stick or switch. $* p < 0.10, ** p < 0.05, *** p < 0.01$.

Table B.10: Regression analysis: Mechanisms in the Religion experiment

	Dep. var.: Switch to source					
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Hindu Source	0.164**	-0.004	-0.009	0.002	-0.009	0.001
	(0.068)	(0.023)	(0.068)	(0.021)	(0.022)	(0.021)
Hindu Source × Quality	-0.238**					
	(0.092)					
Hindu Source × Source is wrong		0.004				
		(0.028)				
Hindu Source × Confidence			0.000			
			(0.001)			
Hindu Source × Guess 1 correct				-0.035		
				(0.036)		
Hindu Source × Dist. to Source					0.000	
					(0.001)	
Hindu Source × Decision time (z)						-0.003
						(0.017)
Quality	0.212***	0.088*	0.092*	0.090*	0.087*	0.072
	(0.068)	(0.049)	(0.049)	(0.049)	(0.049)	(0.052)
Source is wrong	-0.047***	-0.048**	-0.049***	-0.045***	-0.046***	-0.036**
	(0.015)	(0.021)	(0.015)	(0.015)	(0.015)	(0.016)
Confidence	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Guess 1 correct				-0.076***		
				(0.028)		
Dist. to Source					0.002***	
					(0.000)	
Decision time (z)						0.037***
						(0.014)
Constant	0.294***	0.382***	0.383***	0.377***	0.325***	0.367***
	(0.083)	(0.077)	(0.085)	(0.077)	(0.077)	(0.080)
Task controls	✓	✓	✓	✓	✓	✓
Demog. controls	✓	✓	✓	✓	✓	✓
R^2	0.023	0.021	0.021	0.026	0.033	0.029
Dependent variable mean	0.230	0.230	0.229	0.230	0.230	0.224
Observations	4,348	4,348	4,317	4,348	4,348	3,801
Individuals	733	733	733	733	733	729

Notes. The table presents estimates from OLS regressions of switching on the treatment indicator inter-acted with one of six mechanism variables within the *Religion* experiment, controlling for demographics, task parameters, and task order. Demographic controls are the participant's age and dummies for employ-ment, college education and gender. Standard errors are clustered at the participant level. *Quality* is a continuous variable ranging from 0.5 to 0.9. *Source is wrong* =1 if the shown source's estimate is incorrect. Confidence is a participant's confidence in the accuracy of their independent estimate (0 to 100). *Guess 1 correct* = 1 if the participant made a correct first period estimate. *Dist. to source* = $|y_s - y_1|$. *Decision time* is the z-standardised time in seconds taken by participant on the page where they decide whether to stick or switch. $* p < 0.10, ** p < 0.05, *** p < 0.01$.

Table B.11: Regression analysis: Mechanisms in the Minimal experiment

| | Dep. var.: Switch to source | | | | | |
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
In-group Source	0.070	-0.021	-0.039	-0.005	-0.009	-0.011
	(0.120)	(0.032)	(0.078)	(0.029)	(0.034)	(0.027)
In-group Source × Quality	-0.113					
	(0.172)					
In-group Source × Source is wrong		0.037				
		(0.048)				
In-group Source × Confidence			0.000			
			(0.001)			
In-group Source × Guess 1 correct				-0.008		
				(0.053)		
In-group Source × Dist. to Source					0.000	
					(0.001)	
In-group Source × Decision time (z)						0.015
						(0.027)
Quality	0.673***	0.611***	0.621***	0.616***	0.615***	0.557***
	(0.130)	(0.092)	(0.092)	(0.090)	(0.091)	(0.095)
Source is wrong	-0.048*	-0.068*	-0.050*	-0.047*	-0.052**	-0.055**
	(0.026)	(0.035)	(0.026)	(0.026)	(0.026)	(0.026)
Confidence	-0.005***	-0.005***	-0.004***	-0.004***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Guess 1 correct				-0.131***		
				(0.038)		
Dist. to Source					0.002**	
					(0.001)	
Decision time (z)						0.057***
						(0.021)
Constant	0.200	0.249**	0.250**	0.232**	0.190*	0.210**
	(0.126)	(0.100)	(0.107)	(0.100)	(0.102)	(0.106)
Task controls	✓	✓	✓	✓	✓	✓
Demog. controls	✓	✓	✓	✓	✓	✓
R^2	0.113	0.113	0.109	0.122	0.120	0.136
Dependent variable mean	0.312	0.312	0.308	0.312	0.312	0.300
Observations	1,629	1,629	1,613	1,629	1,629	1,461
Individuals	278	278	278	278	278	277

Notes. The table presents estimates from OLS regressions of switching on the treatment indicator interacted with one of six mechanism variables within the *Minimal* experiment, controlling for demographics, task parameters, and task order. Demographic controls are the participant's age and dummies for employment, college education and gender. Standard errors are clustered at the participant level. *Quality* is a continuous variable ranging from 0.5 to 0.9. *Source is wrong*=1 if the shown source's estimate is incorrect. Confidence is a participant's confidence in the accuracy of their independent estimate (0 to 100). *Guess 1 correct*= 1 if the participant made a correct first period estimate. *Dist. to source* $= |y_s - y_1|$. *Decision time* is the z-standardised time in seconds taken by participant on the page where they decide whether to stick or switch. $* p < 0.10, ** p < 0.05, *** p < 0.01$.

Table B.12: Regression analysis: Mechanisms in the Human v Computer experiment

			Dep. var.: Switch to source			
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Computer Source	0.126	0.149***	0.176***	0.159***	0.196***	0.156***
	(0.094)	(0.025)	(0.051)	(0.022)	(0.028)	(0.022)
Computer Source × Quality	0.043					
	(0.135)					
Computer Source × Source is wrong		0.022				
		(0.040)				
Computer Source × Confidence			0.000			
			(0.001)			
Computer Source × Guess 1 correct				-0.008		
				(0.051)		
Computer Source × Dist. to Source					-0.002**	
					(0.001)	
Computer Source × Decision time (z)						-0.044**
						(0.019)
Quality	0.630***	0.641***	0.642***	0.643***	0.644***	0.647***
	(0.072)	(0.063)	(0.063)	(0.062)	(0.063)	(0.066)
Source is wrong	-0.062***	-0.067***	-0.061***	-0.059***	-0.063***	-0.059***
	(0.018)	(0.019)	(0.018)	(0.017)	(0.018)	(0.018)
Confidence	-0.005***	-0.005***	-0.005***	-0.004***	-0.005***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Guess 1 correct				-0.146***		
				(0.022)		
Dist. to Source					0.003***	
					(0.001)	
Decision time (z)						0.051***
						(0.012)
Constant	0.221***	0.214***	0.207***	0.205***	0.157**	0.155**
	(0.075)	(0.071)	(0.071)	(0.071)	(0.072)	(0.076)
Task controls	✓	✓	✓	✓	✓	✓
Demog. controls	✓	✓	✓	✓	✓	✓
R^2	0.134	0.135	0.135	0.145	0.141	0.146
Dependent variable mean	0.365	0.365	0.365	0.365	0.365	0.358
Observations	3,473	3,473	3,473	3,473	3,473	3,130
Individuals	593	593	593	593	593	592

Notes. The table presents estimates from OLS regressions of switching on the treatment indicator interacted with one of six mechanism variables within the *Computer* experiment, controlling for demographics, task parameters, and task order. Demographic controls are the participant's age and dummies for employment, college education and gender. Standard errors are clustered at the participant level. *Quality* is a continuous variable ranging from 0.5 to 0.9. *Source is wrong*=1 if the shown source's estimate is incorrect. Confidence is a participant's confidence in the accuracy of their independent estimate (0 to 100). *Guess 1 correct*= 1 if the participant made a correct first period estimate. *Dist. to source* = $|y_s - y_1|$. *Decision time* is the z-standardised time in seconds taken by participant on the page where they decide whether to stick or switch. $*p < 0.10, **p < 0.05, ***p < 0.01$.

C Experiment details and additional analyses

C.1 Survey module

Demographics. In all experiments, participants provide their age, sex, education level, and employment status. In the *Caste* and *Religion* experiments, participants also state their religion, caste group, religiosity, and their favourite religious festival (free text). These questions also serve as a mild priming device, drawing attention to these characteristics before the main decision tasks (as in Chen et al. (2014)). Participants are only asked these questions after clearing the attention and comprehension tests.

Exposure and Attitudes. Participants in the *Caste* experiments respond to three additional survey questions after they complete the main tasks. The first two elicit the extent to which respondents have close associations with people who belong to their religious or caste out-groups. The questions are:

> How many of your friends belong to the same [Religion/Caste category] as you?

> The final question elicits people's attitudes towards caste-based affirmative action policies.

> Do you support reservations in jobs and educational institutions based on caste?

Beliefs – Group performance. Participants in the *Caste* experiments state their beliefs about the probability that an anonymous person belonging to a caste or religious group will answer the experimental task correctly. These beliefs are incentivised for accuracy – participants earn an additional $0.50 if they guess the number within ±5% points of the true probability, which is calculated based on a previous study. These questions are asked for the "General" and "Scheduled Castes" caste groups.

> If a randomly selected individual belonging to the [Caste group] category attempted the Decision task (the task that you just completed). What do you believe is the probability (0% to 100%) that they will answer it correctly? 0% means that they will never get it correct. 100% means that they will always get it correct.

Reflection question. After completing the survey, respondents provide free text responses to:

> Please tell us how you used the recommendation when making the second decision in the tasks. How did you think about the choice of using your own decision or the shown number?

Individualism. Experiments *Religion, Minimal*, and *Human v. Computer* included 8 additional questions that measured Horizontal and Vertical Individualism. These measures were taken from

the scale developed by Triandis and Gelfand (1998).[13] Answers are coded on a scale from 1 to 5, with 1 indicating "Strongly disagree" and 5 indicating "Strongly agree".

The questions are:

I would rather depend on myself than others.
I rely on myself most of the time. I rarely rely on others.
I often do my own thing.
My personal identity, independent of others, is very important to me.
It is important that I do my job better than others.
Winning is everything.
Competition is the law of nature.
When another person does better than I do, I get tense.

Summing up the responses to these questions results in an "Individualism" score for each participant. I preregistered analyses studying heterogeneity in switching by this individualism measure. The results do not indicate any significant correlations between individualism and the likelihood of switching because of differences in the source's identity.

C.2 Surnames used in the experiments

The recognisability of the Hindu surnames used in the experiments were validated in a separate survey ($N = 350$). These individuals completed much of the training module and comprehension tests that will be used in the main treatments. The source of truth for the incentivisation of these classifications came from official classifications of individuals belonging to these communities, or the common nature of these surnames. The recognisability ranged from $\approx 60\%$ to 85%, with names from the SC/ST/OBC castes being, on average, more recognisable than General caste surnames. The Muslim names were not validated, given the common nature and clear identifiability of these names.

Hindu, General caste names.   Iyer, Banerjee, Chaturvedi, Tiwari, Bharadwaj, Mishra.

Hindu, SC/ST/OBC caste names.   Paraiyar, Bhil, Jatav, Manjhi, Mahar, Chamar.

Muslim names.   Khan, Shaikh, Abdullah, Syed, Moinuddin, Ali.

At the start of the experiment, participants are told that the source's decisions were made by participants in a previous study, which was a true statement. Participants were informed at the end of the study that the names used in Religion and Caste experiments were nicknames, and not the actual names of the people who made the decisions.

C.3 Source decisions

I curate the decisions as follows:

---

[13]The full battery comprises 24 questions, half of which measure individualism and the other half collectivism. In the experiment, the questions regarding collectivism are dropped to avoid making the survey module too lengthy, focusing on the role between individualism and a preference for consistency or autonomy.

- For each task, two decisions are selected such that at least one participant from each relevant identity group made that decisions.

- For each task, one of the decisions is within ±2% of the Bayesian posterior. This is the "correct" answer.

- The second decisions ("incorrect") is chosen to be at least 15% points away from the true value.

For example, 51 and 25 are chosen on task 1. At least one participant from each identity category made these decisions in the pilot experiments.

C.4   Quality signals

Conceptual discussion

The DM forms a belief $\hat{Q}$ about the accuracy Q of y_s. This is the probability that $y_s = y_T$. The DM also has a belief about the accuracy of their own decision, their confidence c, which is the probability that $y_1 = y_T$. Suppose that choosing y_T yields a utility $U = 1$, and that all other choices yield $U = 0$. This gives:

$$E[\text{switch}] = \hat{Q} \cdot 1 - (1 - \hat{Q}) \cdot 0 = \hat{Q}$$
$$E[\text{stick}] = c \cdot 1 - (1 - c) \cdot 0 = c$$

When deciding whether to stick or switch, the only available comparison is between c and $\hat{Q}$, i.e. the DM switches if $E[\text{switch}] > E[\text{stick}]$. This implies that DMs switch if they believe that $\hat{Q} > c$, and stick otherwise.

$$y_2 = \begin{cases} y_s & \text{if } \hat{Q} > c \\ y_1 & \text{if } \hat{Q} \leq c \end{cases}$$

First, consider the case where a DM only sees y_s and has no information about the source's accuracy. If the DM has no prior beliefs about the pool from which sources come from, $\hat{Q} = 1/n$ which means they will only switch if they are very uncertain about their decision.

Now suppose that the social identity (such as a person's race, ethnicity, gender, or political affiliation) g that S belongs to is observable. Models of statistical discrimination show that people make inferences about individuals from beliefs about the characteristics of their social groups. In this case, if the DM has some prior beliefs about the ability of an identity group g they can evaluate the accuracy of the decision y_s based on these beliefs, i.e. $\hat{Q} = Q_g$. Thus, DMs reactions to sources of different identities will be driven by differences in the beliefs held about these groups.[14]

Suppose now that the DM receives a (possibly noisy) signal about the accuracy Q_S of the specific decision y_s made by the source S. The DM's belief about the accuracy of y_s will be a function of their

---

[14]If these beliefs are inaccurate, then this will lead to behaviour resembling inaccurate statistical discrimination (Bohren et al., 2023).

beliefs about the group g and the signal, $\hat{Q} = f(Q_g, Q_S)$. A Bayesian updating rule would predict that these are weighted in proportion to the (beliefs in the) variance of Q_g and Q_S. If Q_S is sufficiently precise then $\hat{Q} = Q_S = Q$, and underlying beliefs about the ability of groups will not play a role in decision-making. In other words, providing a precise signal of the quality of the decision made by the source will eliminate the role of any group-specific beliefs in this situation. This yields the following predictions when a signal of quality is provided:

Prediction. *Switching increases with an increase in beliefs about information quality (Q_S). When Q_S is precise, switching is uncorrelated with Q_g.*

Given a precise signal, any observed differences in switching because of a difference in source's identity can be attributed to differences in k because of different group identities, which can be interpreted as preferences for one group relative to another. The signal essentially converts the switching decision into a lottery, and breaks the link between beliefs about information quality and preferences for the identity of the source.

Instructions

In experiment *Caste*, the following information is shown to participants:

> There is a [Q] % chance that this number is the correct answer.
>
> The computer has access to a pool of participants who made correct guesses on this exact task in a previous study. They had the same information and saw the same balls as you when making their guess. The computer randomly chooses one of these people and shows you a number:
>
> - With [Q]% probability, the shown number is the chosen person's correct guess.
> - Otherwise, the shown number is incorrect.

In the *Computer* treatment, the following information is shown to participants:

> There is a [Q] % chance that this value is within ±2% points of the correct answer.
>
> Otherwise, the computer chooses a random number between 0 and 100.

In all other experiments, the following information is shown to participants:

> There is a [Q] % chance that this guess is within ±2% points of the correct answer.
>
> A computer randomly chooses this guess from the guesses made on this exact task by participants in a previous study - they had the same information, and saw the same ball colours when making their guess.

In all of the above cases, Q is a placeholder for the randomly chosen probability that the source's decision is correct (i.e. participants always see the probability).

Experiment *Caste – No Signal*

The following information is presented to participants in this experiment group instead of the quality signal:

> The computer has access to a pool of participants who made guesses on this exact task in a previous study. They had the same information and saw the same balls as you when making their guess. The computer randomly chooses one of these people and shows you the chosen person's guess.

C.5   Experiment *Caste – No signal*

This experiment was conducted at the same time and participants were recruited from the same sampling pool as the *Caste* experiment. Participants were given a quality signal in the *Caste* experiment, but not in *Caste – No Signal*.

Learning with and without a signal

A comparison of decisions in these experiments shows that participants switch more when given the quality signal. The difference is more pronounced when the signal is stronger – Appendix Figure C.1 shows that when source quality is low (50%), switching in the two experiments differs by $\approx$ 11%. When the source quality is high (90%), the difference is $\approx$ 22%.

Preference channel

The results on beliefs in Sections 2.4 and 3 show that in the absence of a quality signal, participants may rely on underlying beliefs about the performance of different caste groups (which are higher for the General caste group). Does learning because of the caste identity of the source differ within experiment *Caste – No Signal*? Appendix Table C.1 shows the results from estimating the specification in Equation 1 for this experiment. The results show that the estimated treatment effect is not statistically significant – participants do not appear to switch differently whether they see a General Caste or a SC/ST/OBC source.

To place these results in perspective, note that in the *Caste* experiment a 40% (exogenous) increase in source quality leads to $\approx$ 6% increase in switching. In comparison, participants' beliefs about the differences in ability between the two caste groups is much smaller (about $5-10\%$). Thus, in the absence of preferences for the caste identity of information sources, this experiment (with a sample size of 295 participants) is underpowered to detect differences in switching because of the relatively small difference in beliefs about the performance of different groups.

Figure C.1: Switching with and without the quality signal
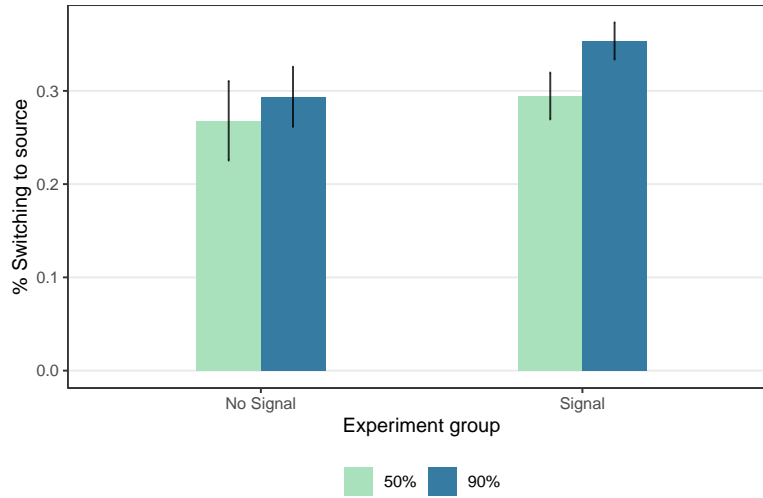
Notes. The bars shows the percentage of participants switching to the source at different levels of signal quality. In the first group, signal quality is not revealed to participants (experiment *Caste – No Signal*). In the second group, participants are informed of the signal quality (experiment*Caste*). Error bars indicate 95% confidence intervals.

Table C.1: Regression analysis: Experiment *Caste – No Signal*.

	Dep. var.: Switch to source			
	(i)	(ii)	(iii)	(iv)
General Caste Source	-0.025	-0.021	-0.021	-0.021
	(0.034)	(0.034)	(0.034)	(0.034)
Quality		0.034	0.019	0.019
		(0.022)	(0.024)	(0.024)
Confidence		-0.002***	-0.002***	-0.002***
		(0.001)	(0.001)	(0.001)
Source is wrong			-0.035	-0.035
			(0.025)	(0.025)
General Caste				0.000
				(0.038)
Constant	0.285***	0.452***	0.474***	0.474***
	(0.025)	(0.105)	(0.104)	(0.104)
Task controls		✓	✓	✓
Demog. controls		✓	✓	✓
R^2	0.001	0.031	0.032	0.032
Dependent variable mean	0.273	0.273	0.273	0.273
Observations	1,719	1,719	1,719	1,719
Individuals	295	295	295	295

Notes. Average treatment effects in the Caste – No Signal experiment. In this experiment, source quality is not observable by participants. Controls are task and order fixed effects, and demographic characteristics(the participant's age and dummies for employment, college education and gender). Standard errors are clustered at the participant level. $* p < 0.10, ** p < 0.05, *** p < 0.01$.

D Experiment instructions

Experiment *Caste – Quality*

Welcome

This study is being conducted by researchers from the Norwegian School of Economics. It will take about 10 minutes to complete this study. Please read all questions and instructions carefully.

Payment and Bonus Rewards

- You can earn up to **$ 3.5 (~ INR 290)** in additional bonuses depending on your task performance. You will be given information about the bonuses as you progress through the study.
- If you want to be eligible for the bonus, you must complete the entire study. The bonus that you earn will be shown to you at the end of the study, and will be processed and sent to you within 7 working days.
- You will need to read all the instructions carefully and answer a comprehension test correctly in order to participate in the study and be eligible for bonuses. You will have two chances to complete the comprehension test. In case you do not pass the comprehension test, you will not be eligible for any rewards.
- Bonus rewards will be paid in points, equivalent to the US dollar amount.

Guidelines

- We encourage you to try to answer all questions accurately and truthfully.
- This study is confidential and will only be used for research purposes.
- This study has been approved by an institutional review board.
- You may write to us at s14117@nhh.no in case you have any queries about this study.

Consent

By participating in this study you agree to the usage of your anonymised information and actions within the survey for research purposes.

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[Next]

Figure D.1: Welcome and consent

Instructions for the Decision Tasks (1/3)

You will do 6 of these tasks, and in each task, you will make two decisions. The instructions below apply to all tasks.

Task Description

In each task, there are two bags - a **RED** bag and a **BLACK** bag. Each bag contains 100 balls, which are either **Red** or **Black**. The **RED** bag always contains more Red balls, and the **BLACK** bag contains more black balls. You know how many balls of each colour are in a bag.

One of the bags is chosen at random, but you do not know which bag is chosen. A few balls are drawn randomly from the chosen bag. Balls are drawn one by one, and they are put back into the bag before the next one is drawn.

You are shown the colours of all the balls that were drawn from the bag. You also know the chance with which a bag can be chosen, and the number of red and black balls in each bag.

You will make **two** decisions on each task. Both decisions are **eligible for a bonus reward.**

The First Decision

Based on the composition of the bags and the colours of the drawn balls, you have to **guess the likelihood that the balls were drawn from the RED bag. This should be a number between 0 and 100 %.** 0 means that you think there is no chance the balls were drawn from the red bag, and 100 means that you are completely certain that the balls were drawn from the red bag.

[Next]

Figure D.2: Instructions 1/3

Instructions for the Decision Tasks (2/3)

After making the first decision, you will be shown a number.

How is this number generated?

- The computer has access to a pool of participants who made **correct guesses** on this exact task in a previous study. They had the same information and saw the same balls as you when making their guess.
- The computer randomly chooses one of these people, and shows you a number:
    - With some probability, the shown number is the chosen person's **correct** guess.
    - Otherwise, the shown number is **incorrect**.

The probability that the correct guess is shown can change from task to task.

The Second Decision

You have to make a choice:

1. Stick to your first guess, OR
2. Switch to the shown number.

Next, you will learn about how you can earn bonuses on these tasks.

Next

Figure D.3: Instructions 2/3

Instructions for the Decision Tasks (3/3)

Bonuses

- You will do 6 of these tasks, making 2 decisions in each task. **One** of these 12 decisions will be randomly selected for a bonus.
- Each task has a mathematically correct answer.
- If the chosen guess is **within ± 2 % points of the correct answer**, your bonus will be $ 3.
- If your guess is more than 2 % away from the correct answer, then you will not earn a bonus.

It is therefore in your best interest to try and make all your guesses as accurately as possible.

Note: The correct answer to each task can be calculated using a probability formula. Click to see formula

Next, you will see an example task.

Next

Figure D.4: Instructions 3/3

Example Task (1/3)

This is an example of how the actual task will work.

Example Task

One of these bags is selected.
The **RED** bag is selected with a **50%** chance.

RED bag	**BLACK** bag
100 **Red**, 0 **Black** balls	0 **Red**, 100 **Black** balls
50% chance of being selected	50% chance of being selected

When you click the button, **3 balls** will be drawn from the selected bag one by one, with replacement. You will be allowed to make your guess after drawing the balls.

Click to draw balls

Figure D.5: Example 1/3

Example Task (1/3)

This is an example of how the actual task will work.

Example Task

One of these bags is selected.
The **RED** bag is selected with a **50%** chance.
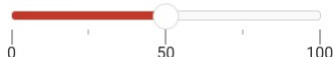
RED bag	**BLACK** bag
100 **Red**, 0 **Black** balls	0 **Red**, 100 **Black** balls
50% chance of being selected	50% chance of being selected

When you click the button, **3 balls** will be drawn from the selected bag one by one, with replacement. You will be allowed to make your guess after drawing the balls.

The 3 balls are: ● ● ●

Make your Guess

Based on the information above, **state your guess (0-100%) that expresses how likely you think it is that the RED bag was selected**. Use the slider to select your answer.

```
|------------●----------|
0          50          100
```

[   ] %

This example is also an attention check. The correct answer for this example is 100. Please select 100 to continue.

[Next]

Figure D.6: Example 1/3

Example Task (2/3)

After making the first decision, you will be taken to a page that looks like the one below.

Here, you have to use the slider to tell us how certain you are that the decision that you made on the previous screen is within ±2 % points of the correct answer. A value of 0 % means that you are not at all certain. 100 % means that you are completely certain.

Example Task

Your first guess was: **100 %** that the the **RED** bag was selected.

How **certain** are you that that your guess is within ±2 % points of the correct answer? Use the slider to select your answer.

```
|●----------------------|
Very uncertain    50%    Very certain
```

[   ] %

[Next]

Figure D.7: Example 2/3

Example Task (3/3)

The example continues on this page - no bonuses will be awarded for this task, but you have to provide an answer to continue to the next page.

Example Task - The Second Decision

The computer shows:

Study Participant
73

There is a **50 % chance** that this number is the correct answer.

More info:

- The computer has access to a pool of participants who made **correct guesses** on this exact task in a previous study. They had the same information and saw the same balls as you when making their guess.
- The computer randomly chooses one of these people, and shows you a number:
  - With some probability, the shown number is the chosen person's **correct** guess.
  - Otherwise, the shown number is **incorrect**.

Make your Second Decision

Your first guess was: **100 %**.

Based on the information above, **choose one of these options to make your decision (0-100%) that expresses how likely you think it is that the RED bag was selected**.

○ **100 %** - Stick to your first guess
○ **73 %** - Switch to the shown number

[Next]

Figure D.8: Example 3/3

Summary

Congratulations! You have successfully completed the example task.

Next, you will answer a short comprehension test. You must pass the test in order to be eligible for survey completion and bonus payments. Below is a short summary of the task, please familiarise yourself with them before moving on to the test.

Task Description

There are two bags - a **RED** bag and a **BLACK** bag. Each bag contains 100 balls, which are either **Red** or **Black**. The **RED** bag always contains more Red balls, and the **BLACK** bag contains more black balls. You know how many balls of each colour are in a bag.

One of the bags is chosen at random, and a few balls are drawn randomly from the chosen bag. Balls are drawn one by one, and they are put back into the bag before the next one is drawn. You are shown the colours of all the balls that were picked.

First decision: Based on this information, you have to **guess the likelihood that the balls were drawn from the RED bag. This should be a number between 0 and 100 %.**

Second decision: The second decision is made after you see what someone else has guessed on the exact same task. They have seen the same bags and drawn balls as you. A computer will show you a number. You have to decide whether to stick to your first guess, or switch to the shown number.

Important points

1. You make two decisions on each task, and there are 6 tasks.
2. Each of the Decision Tasks has a mathematically correct answer.
3. One of the decisions will be randomly chosen for a bonus. You will get a $ 3 bonus if the chosen decision is within 2% points of the correct answer.

Click the button to proceed to the comprehension test.

[Next]

Figure D.9: Summary

Task Comprehension: First Attempt

You must answer all questions to proceed. You have two chances to do this. If you are unable to pass, the assignment will end immediately and you will not be eligible for approval or for any bonus rewards.

Click here to review the instructions.

1. You will make several guesses in the tasks. What exactly are you guessing?

◯ A number between 0-100, representing your guess about the chance that the RED bag was selected.
◯ The probability of a green ball being drawn.

2. Which decision will be used to calculate the bonus?

◯ The first decision
◯ The last decision
◯ One randomly chosen decision

3. If a decision is selected for the bonus, you will get the bonus ...

◯ If the selected decision is within 2 % points of the mathematically correct value.
◯ By correctly guessing the hard disk capacity of the computer.

4. Before making your second decision, the computer will show you a number. Which of these statements is correct?

◯ The shown number is always a random number.
◯ The shown number is either another person's correct guess, else it is an incorrect answer.

[Next]

Figure D.10: Comprehension (two attempts)

Survey questions

Please answer the following questions (all questions are mandatory). Accurate answers to these questions will help us in our research.

Age (in years)

[   ]

Gender

○ Female
○ Male
○ Other

Highest education level attained/in progress?

○ None
○ Primary
○ Secondary
○ Bachelors degree/diploma
○ Above Bachelors

Current employment status

○ Employed - Full time job
○ Employed - Part time job
○ Self-employed
○ Not currently employed

Which state are you from?

[--------   ⌄]

Which religion do you belong to?

○ Buddhist
○ Christian
○ Hindu
○ Jain
○ Muslim
○ Sikh
○ Other
○ None/prefer not to say

Which category do you belong to?

○ General
○ SC (Scheduled Castes)
○ ST (Scheduled Tribes)
○ OBC (Other Backward Class)
○ Prefer not to say

Which is the most important religious festival for you?

[   ]

How important is religion in your life?

○ Not at all important
○ Not very important
○ Somewhat important
○ Very Important
○ I do not want to answer

[Next]

Figure D.11: Demographics

Figure D.12: In-between decision tasks

Decision Task 1 of 6

One of these bags is selected.
The **RED** bag is selected with a **50%** chance.

RED bag	**BLACK** bag
70 **Red**, 30 **Black** balls	30 **Red**, 70 **Black** balls
50% chance of being selected	50% chance of being selected

When you click the button, **5 balls** will be drawn from the selected bag one by one, with replacement. You will be allowed to make your guess after drawing the balls.

Click to draw balls

Make your Decision

Based on the information above, **state your guess (0-100%) that expresses how likely you think it is that the RED bag was selected**. Use the slider to select your answer.

0   50   100

___ %
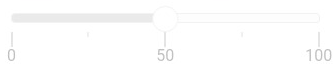
Next

Figure D.13: Decision Tasks - First guess

Decision Task 1 of 6

One of these bags is selected.
The RED bag is selected with a 50% chance.

RED bag	BLACK bag
70 Red, 30 Black balls	30 Red, 70 Black balls
50% chance of being selected	50% chance of being selected

When you click the button, **5 balls** will be drawn from the selected bag one by one, with replacement. You will be allowed to make your guess after drawing the balls.

The 5 balls are: ● ● ● ● ●

Make your Decision

Based on the information above, **state your guess (0-100%) that expresses how likely you think it is that the RED bag was selected**. Use the slider to select your answer.

0   50   100

[   ] %
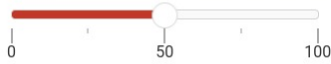
Next

Figure D.14: Decision Tasks - First guess

Decision Task 1 / 6

Your first guess was: **87 %** that the the RED bag was selected.

How **certain** are you that that your guess is within ±2 % points of the correct answer? Use the slider to select your answer.

Very uncertain   50%   Very certain

[   ] %
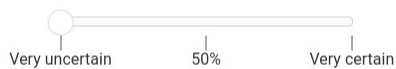
Next

Figure D.15: Decision Tasks - certainty elicitation

Task 1 of 6: Second Decision

1 of 6

See task details

When you click the button, the computer will show you a number. You will be allowed to make your decision after clicking the button.

Click to proceed

Figure D.16: Decision Tasks - Second decision

Task 1 of 6: Second Decision

See task details

The computer shows:

Mr. P. Manjhi

3

There is a **50 % chance** that this number is the correct answer.

More info about this guess:

- The computer has access to a pool of participants who made **correct guesses** on this exact task in a previous study. They had the same information and saw the same balls as you when making their guess.
- The computer randomly chooses one of these people, and shows you a number:
  - With 50% probability, the shown number is the chosen person's **correct** guess.
  - Otherwise, the shown number is **incorrect**.

Make your decision

Your first guess was: **5 %**.

Based on the information above, **choose one of these options to make your guess (0-100%) that expresses how likely you think it is that the RED bag was selected**.

○ **5 %** - Stick to your first guess
○ **3 %** - Switch to the shown number

Next

Figure D.17: Decision Tasks - Second decision

Survey Questions

You have successfully completed the Decision task.

Next, please answer a few questions based on the task that you just completed.

Click the button to continue.

Next

Figure D.18: Survey section

Task Reflection

Please tell us what you thought about when making the second decisions in the tasks. How did you think about the choice of using your own decision or the shown number?

Please provide a detailed response (about 20 words).

Word count:

Next

Figure D.19: Reflection question

Survey Questions

Please answer the following questions (all questions are mandatory). Accurate answers to these questions will help us in our research.

How many of your close friends have the same religion as you?
- ○ All of them
- ○ Most of them
- ○ Some of them
- ○ Hardly any of them

How many of your close friends belong to the same caste category as you?
- ○ All of them
- ○ Most of them
- ○ Some of them
- ○ Hardly any of them

Are you in favour of caste-based reservations?
- ○ Strongly in favor
- ○ Somewhat in favor
- ○ Somewhat against
- ○ Strongly against

Next

Figure D.20: Survey questions

Survey Questions

Now, you will be shown 2 questions where you have to guess the performance of people on the Decision task.

You can earn a bonus reward from these questions: One of the questions will be randomly selected for a bonus. If your answer to this question was correct, you will earn a $0.50 reward.

A correct answer to this question is an answer that is **within ±5 %** of the actual value. The actual value will be calculated from the responses provided by participants in a previous study. You will be shown the bonus amount for this part on the last page of this survey.

Click the button to continue.

Next

Figure D.21: Belief elicitation

Survey Questions

Question:

If a randomly selected individual belonging to the **Scheduled Castes** category attempted the Decision task (the task that you just completed). What do you believe is the probability (0% to 100%) that they will answer it correctly?

0% means that they will never get it correct. 100% means that they will always get it correct.

Never (0%)   50%   Always (100%)

[   ] %
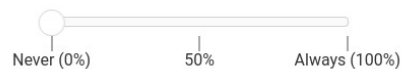
Next

Figure D.22: Belief elicitation

Thank you

You have successfully completed the study. We will process the data and a bonus will be sent to you in a few working days, if applicable.

Your Bonus

You have earned a **$ 0** bonus payment based on your performance on the selected decision. Decision 1 of Task 3 was selected for the bonus.

You have earned a **$ 0** bonus payment based on your performance on the bonus survey question.

Please click the button at the bottom of the page to complete the study. You must click the button to receive credit for your participation.

Some additional info about the task (in case you are curious):

- The correct answers in the task could be calculated using Bayes' law. We will randomly choose one of the guesses that you made and compare it with the correct answer for that task to calculate your bonus.
- We will check your responses, and will process bonus payments if your answers meet the specified criteria.
- The guesses were indeed made by actual participants in a previous study. However, the names used in the recommendations were fictional nicknames.

Next

Figure D.23: Thank you and debriefing page

Caste – No Quality

Instructions for the Decision Tasks (2/3)

After making the first decision, you will be shown a number.

How is this number generated?

- The computer has access to a pool of participants who made guesses on this exact task in a previous study. They had the same information and saw the same balls as you when making their guess.
- The computer randomly chooses one of these people and shows you the chosen person's guess.

The Second Decision

You have to make a choice:

1. Stick to your first guess, OR
2. Switch to the shown number.

Next, you will learn about how you can earn bonuses on these tasks.

Next

Figure D.24: Instructions 2/3

Example Task (3/3)

The example continues on this page - no bonuses will be awarded for this task, but you have to provide an answer to continue to the next page.

Example Task - The Second Decision

The computer shows:

Study Participant

73

More info:

- The computer has access to a pool of participants who made guesses on this exact task in a previous study. They had the same information and saw the same balls as you when making their guess.
- The computer randomly chooses one of these people and shows you the chosen person's guess.

Make your Second Decision

Your first guess was: **100 %**.

Based on the information above, **choose one of these options to make your decision (0-100%) that expresses how likely you think it is that the RED bag was selected**.

- ○ **100 %** - Stick to your first guess
- ○ **73 %** - Switch to the shown number

Next

Figure D.25: Example 3/3

Task Comprehension: First Attempt

You must answer all questions to proceed. You have two chances to do this. If you are unable to pass, the assignment will end immediately and you will not be eligible for approval or for any bonus rewards.

Click here to review the instructions.

1. You will make several guesses in the tasks. What exactly are you guessing?

- ○ A number between 0-100, representing your guess about the chance that the RED bag was selected.
- ○ The probability of a green ball being drawn.

2. Which decision will be used to calculate the bonus?

- ○ The first decision
- ○ The last decision
- ○ One randomly chosen decision

3. If a decision is selected for the bonus, you will get the bonus ...

- ○ If the selected decision is within 2 % points of the mathematically correct value.
- ○ By correctly guessing the hard disk capacity of the computer.

4. Before making your second decision, the computer will show you a number. Which of these statements is correct?

- ○ The shown number is a random number.
- ○ The shown number is another person's guess.

Next

Figure D.26: Comprehension - No Quality

Task 1 of 6: Second Decision

See task details

The computer shows:

Mr. M. Chamar

93

More info about this guess:

- The computer has access to a pool of participants who made guesses on this exact task in a previous study. They had the same information and saw the same balls as you when making their guess.
- The computer randomly chooses one of these people and shows you the chosen person's guess.

Make your decision

Your first guess was: **88 %**.

Based on the information above, **choose one of these options to make your guess (0-100%) that expresses how likely you think it is that the RED bag was selected**.

○ **88 %** - Stick as your first guess
○ **93 %** - Switch to the shown number

Next

Figure D.27: Decision Tasks in *No Quality* - Second decision

Differences in other experiments

The text used to communicate the quality of the source's estimate was different in experiment *Religion, Minimal, Choice,* and *Computer*. The following screenshots are the instruction screens used in those experiments.

Instructions for the Decision Tasks (4/4)

The example continues on this page - no bonuses will be awarded for this task, but you have to provide an answer to continue to the next page. Below, you will see how to make the second decision.

The second decision

Once you submit your first decision, you will see a page similar to the one below. Here you will see another person's guess on the **same** task. This guess is drawn from a pool of guesses on this task, made by participants in a previous study.

This guess will be randomly chosen by a computer program. There is a chance with which the selected guess will be within ± 2% of the correct answer. You then have to make a choice - your second decision can be:

1. The same as your first guess, OR
2. The same as the guess made by someone else.

Remember: Each decision you make is equally likely to be chosen for the bonus, so choose the value that you think is correct.

To proceed with making your decision, click the button below. You will see a guess made by someone else on the same task.

[Click to proceed]

Figure D.28: Decision Tasks in *Religion* - Instructions

The other person's guess

Mr. P. Mishra

Their Guess: 23%

There is a **60 % chance** that this guess is within ± 2 % points of the correct answer.

More info about this guess: A computer randomly chooses this guess from the guesses made on this exact task by participants in a previous study - they had the same information, and saw the same ball colours when making their guess.

Make your decision

Your first guess was: **100 %**.

Based on the information above, **choose one of these options to make your guess (0-100%) that expresses how likely you think it is that the RED bag was selected**.

○ **100 %** - Same as your first guess
○ **23 %** - Same as Mr. P. Mishra

Next

Figure D.29: Decision Tasks in *Religion* - Second guess

Task 1 of 6: Guess 2

One of these bags is selected.
The **RED** bag is selected with a **90%** chance.

RED bag	**BLACK** bag
70 **Red**, 30 **Black** balls	30 **Red**, 70 **Black** balls

90% chance of being selected   10% chance of being selected

The 5 balls are: 🔴🔴⚫🔴🔴

The other person's guess

Study Participant

Their Guess: 97%

There is a **70 % chance** that this guess is close to the correct answer.

More info about this guess:

- This guess is chosen from the guesses made on this exact task by participants in a previous study.
- The computer chooses a guess that is within ± 2 % points of the correct answer with a **70 %** chance.
- This guess was made by someone who had the same information, and saw the same ball colours as you when making their guess.

Make your decision

Your first guess was: **72 %**.

Based on the information above, **choose one of these options to make your guess (0-100%) that expresses how likely you think it is that the RED bag was selected**.

○ **72 %** - Same as your first guess
○ **97 %** - Same as the seen guess

Next

Figure D.30: Decision Tasks in *Choice* - Second guess

Figure D.31: Decision Tasks in *Minimal* - Klee/Kandinsky task

## Instructions for the Decision Tasks (4/4)

The example continues on this page - no bonuses will be awarded for this task, but you have to provide an answer to continue to the next page. Below, you will see how to make the second decision.

The second decision

Once you submit your first decision, you will see a page similar to the one below. Here you will see a value that is chosen by a computer program in the following way: The computer chooses a value that is within ± 2 % points of the correct answer with some probability. Otherwise, the computer chooses a random number between 0 and 100. You then have to make a choice. You can choose your second decision to be:

1. The same as your first guess, OR
2. The same as the value generated by the computer.

Remember: Each decision you make is equally likely to be chosen for the bonus, so choose the value that you think is correct.

<div style="text-align:center">

Computer

Answer: 70%

</div>
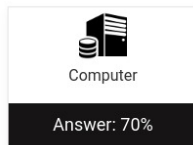
There is a **60 % chance** that this value is within ± 2 % points of the correct answer.

More info: The computer chooses a value that is within ± 2 % points of the correct answer with a **60 %** chance. Otherwise, the computer chooses a random number between 0 and 100.

Make your Second Decision

Your first guess was: **100 %**.

Based on the information above, **choose one of these options to make your decision (0-100%) that expresses how likely you think it is that the RED bag was selected**.

○ **100 %** - Same as your first guess
○ **70 %** - Same as the computer

Next, there will be a comprehension test to check whether you have understood these instructions clearly.

Next

Figure D.32: Instructions in *Computer* - Second guess

67

Task 1 of 6: Guess 2

One of these bags is selected.
The **RED** bag is selected with a **90%** chance.

RED bag	**BLACK** bag
90 **Red**, 10 **Black** balls	10 **Red**, 90 **Black** balls

90% chance of being selected   10% chance of being selected

The 3 balls are: ● ● ●

The computer says...

Computer

Answer: 3%

There is a **90 % chance** that this value is close to the correct answer.

More info:

- The computer chooses a value that is within ± 2 % points of the correct answer with a **90 %** chance.
- Otherwise, the computer chooses a random number between 0 and 100.

Make your decision

Your first guess was: **78 %**.

Based on the information above, **choose one of these options to make your guess (0-100%) that expresses how likely you think it is that the RED bag was selected**.

○ **78 %** - Same as your first guess
○ **3 %** - Same as the computer

Next

Figure D.33: Decision Tasks in *Computer* - Second guess