Wordless Wisdom: The Dominant Role of Tacit Knowledge in True and Fake News Discrimination

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Abstract

In this preregistered study, we investigated the type of knowledge people use to discriminate between true and fake news by asking participants (*N* = 327 Prolific users residing in the United States) to rate the veracity of different news headlines and indicate what decision strategy they used to make each rating (*guess*, *intuition*, *familiarity*, *prior knowledge*, *rule*, or *other*). We found that participants discriminated well between true and fake news headlines, and predominantly chose decision strategies that suggested they were using tacit knowledge (knowledge that is not easily articulated) rather than explicit knowledge (knowledge that is easily articulated). For example, *guess* and *intuition* were chosen 63% of the time, and participants' discrimination was good even when they claimed to be guessing. The fact that tacit knowledge formed the dominant basis of participants' discriminative ability speaks to the types of interventions that may be successful in improving this skill.

Keywords: Fake news, tacit knowledge, explicit knowledge, metacognition, receiver operating characteristic analysis, linear mixed models

General Audience Summary

There has been no research on whether people use tacit knowledge (knowledge that is not easily articulated) or explicit knowledge (knowledge that is easily articulated) to distinguish between true and fake news. This might explain why several interventions designed to improve people's ability to detect fake news, and thus tell it apart from true news, have had limited success. Without understanding how people discriminate between true and fake news, how can we make informed attempts to improve their ability to do so? Consequently, we decided to investigate the nature of knowledge underpinning such discrimination. To do this, we asked 327 U.S. adults to rate the veracity of various news headlines. After each veracity rating, participants indicated the decision strategy they used, which could be one of the following: *guess*, *intuition*, *familiarity*, *prior knowledge*, *rule*, or *other*. We found that participants chose *guess* and *intuition* 63% of the time, but only chose *rule* and *prior knowledge* 21% of the time. Furthermore, participants discriminated between true and fake news headlines well even when they claimed to be guessing. These results suggest that participants mostly used tacit rather than explicit knowledge to discriminate between true and fake news headlines, which speaks to the types of interventions that may be successful in improving this skill. Specifically, giving people explicit guidance to help them detect fake news and thus tell it apart from true news may not be effective because it will likely require explicit knowledge, which they are only occasionally using in the first place. Instead, to develop effective interventions for improving true and fake news discrimination, we recommend applying the techniques used to improve our tacit knowledge in everyday life, such as when learning new languages, instruments, or sports. Examples of these techniques include, but are not limited to, mentorship and repeated practice.

Wordless Wisdom: The Dominant Role of Tacit Knowledge in True and Fake News Discrimination

A core issue regarding fake news is its potential to masquerade as true news. Indeed, if we were all perfect classifiers of true and false information, fake news might be less problematic. However, as demonstrated by the countless tragedies thought to be fueled by fake news, such as the January 6 U.S. Capitol attack (Calvillo et al., 2021b) and outbreaks of vaccine-preventable diseases (Frenkel, 2021), this perfect classification eludes us. As a result, there has been a recent surge in research aimed at discovering why people believe fake news (Ecker et al., 2022; Pennycook & Rand, 2021), as well as what can be done to prevent this. The latter line of inquiry has garnered particular attention, with researchers creating interventions aimed at improving people's ability to detect false or misleading information (and consequently tell it apart from credible information) in an attempt to combat its harmful consequences (Clayton et al., 2020; Modirrousta-Galian et al., 2023; Roozenbeek & van der Linden, 2019).

Surprisingly, however, there has been little attention devoted to uncovering the nature of knowledge people use to discriminate between true and fake news. This might be an oversight as it potentially speaks to the types of interventions that are likely to be successful. Without understanding how people distinguish between true and fake news, how can we make informed attempts to improve their ability to do so? Failure to understand the underlying knowledge behind true and fake news discrimination may explain why several interventions designed to mitigate the influence of fake news have had limited success. For example, inductive learning interventions have so far produced null effects (Modirrousta-Galian et al., 2023). More worryingly, general warnings about misleading information on social media have been shown to reduce people's belief in both true and fake news (Clayton et al., 2020). Similarly, Bad News and Go Viral!, two popular gamified inoculation interventions, have been shown to cause people to rate *both* true *and* fake news as less reliable or more manipulative (Modirrousta-Galian & Higham, 2023; Rędzio et al., 2023). Failure to believe credible information could be just as harmful as believing false information.

For example, the aforementioned outbreaks of vaccine-preventable diseases can be driven by both belief in false information (e.g., vaccines contain poisons) and a lack of belief in credible information (e.g., vaccines confer resistance against diseases; Dubé et al., 2013).

Accordingly, to understand how people distinguish between true and fake news, and thus inform our efforts to reduce the impact of fake news, we investigated the nature of knowledge underpinning such discrimination. In line with research in cognitive psychology, we distinguish between two different types of knowledge: implicit and explicit. Implicit knowledge can be thought of as knowledge that is “stored without awareness and therefore … not easily articulated” (VandenBos, 2015, p. 1063). However, whether implicit knowledge represents knowledge without conscious awareness is an ongoing debate amongst researchers (Davies, 2015; Higham et al., 2000; Kihlstrom, 1994). To avoid confusion and unsubstantiated claims about participants’ states of consciousness, we instead refer to explicit versus tacit to describe knowledge that is versus is not easily articulated, respectively. For example, news discrimination that relies on simple, describable rules would constitute explicit knowledge, whereas news discrimination that relies on intuition would constitute tacit knowledge.

There are various ways to measure tacit and explicit knowledge (Ellis & Roever, 2021). One is through self-report measures sometimes used in implicit learning experiments (Dienes & Scott, 2005; Neil & Higham, 2012; Scott & Dienes, 2008; Ziori et al., 2014). In implicit learning studies that use artificial grammars, participants are first exposed to multiple exemplars of letter strings (e.g., MVXRT) that conform to a finite state grammar. Then, in a test phase, participants indicate whether a new set of exemplars follow the same grammatical structure as those from the training phase. In some studies, participants indicate after each classification what decision strategy they used to make their judgement. For example, Scott and Dienes (2008) asked participants to choose one of the following: *guess*, *intuition*, *rule*, *familiarity*, or *memory*. The *guess* and *intuition* decision strategies were interpreted as being indicative of tacit knowledge, whereas the *rule* and *memory* decision strategies were interpreted as being indicative of explicit knowledge. With this procedure, the guessing criterion can also be measured to further assess the nature of knowledge acquired. Specifically, if participants' classification accuracy is significantly above chance level when they report that they are guessing, that is considered to show evidence of tacit knowledge (Dienes, 2007).

The present preregistered study applied this self-report method of measuring tacit and explicit knowledge to a true and fake news discrimination task. Participants rated the veracity of various news headlines on a scale ranging from 1 (*high confidence false*) to 6 (*high confidence true*). After each veracity rating, participants indicated the decision strategy they used, which could be one of the following: *guess*; *intuition*; *familiarity*; *prior knowledge*; *rule*; or *other*. The *guess*, *intuition*, *rule*, and *familiarity* decision strategies were adapted from Scott & Dienes (2008), and the *prior knowledge* decision strategy was adapted from Ziori et al. (2014). We added *other* in case participants used a decision strategy we had not considered. Following previous work (Dienes & Scott, 2005; Scott & Dienes, 2008; Ziori et al., 2014), we interpreted the *guess* and *intuition* decision strategies to be indicative of tacit knowledge, and the *rule* and *prior knowledge* decision strategies to be indicative of explicit knowledge. We also measured the guessing criterion to further assess the nature of knowledge used by participants to distinguish between true and fake news.

Method

Transparency and Openness

All data, analytic code, and materials needed to replicate this study are available on OSF (https://osf.io/qfe3g/). This study was preregistered (https://aspredicted.org/n7v2z.pdf). We obtained ethical approval to conduct this study from the University of Southampton Faculty of Environmental and Life Sciences Ethics Committee (65104.A2). We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study.

Participants

After excluding two participants for exiting full screen mode more than five times, 25 participants for withdrawing consent, and four participants for timing out, our final sample consisted of 327 participants from Prolific (https://www.prolific.co/). We used Prolific because it provides a large pool from which to recruit U.S. participants. The sample size was based on an a priori power analysis in G*Power that indicated 327 participants were required to detect a small effect with a two-tailed one-sample *t*-test ($n \approx 327$, $d = 0.20$, $1- \beta = .95$, $\alpha = .05$). All participants resided in the United States at the time of the study, were between the ages of 18 and 65, fluent in English, approximately balanced in terms of sex, and had a minimum Prolific approval rate of 90%. Participants that took part in our previous fake news studies on Prolific were excluded from this research. Participants were paid at a rate of £6.00 per hour. See Table 1 for a complete overview of the sample demographics.

Table 1

Sample Demographics

Demographic variable	*n*	%
Gender		
Female	159	48.62
Male	160	48.93
Other	7	2.14
Prefer not to say	1	0.31
Age		
18–29	94	28.75
30–39	99	30.28
40–49	65	19.88
50–59	45	13.76
60–65	24	7.34
Political orientation		
1	50	15.29
2	68	20.80
3	62	18.96
4	66	20.18
5	56	17.13
6	19	5.81
7	6	1.83

Note. Political orientation was measured on a scale that ranged from 1 (*very left-wing*) to 7 (*very right-wing*). The sample had an age range of 18 to 65 ($M = 38.29$, $SD = 12.16$).

Materials

We used a set of 95 news items (48 true and 47 fake). We obtained these from Chen et al. (2023), Study 3, in which participants rated 278 news items (157 true and 121 fake) on several dimensions. One of these dimensions was a 6-point Likert scale that ranged from 1 (*more favorable to Democrats*) to 6 (*more favorable to Republicans*). After calculating the average partisanship rating for each headline, we found that most favored Democrats. Therefore, we randomly sampled 25 true and 25 fake news headlines with average partisanship ratings between 3 and 3.5, and an additional 25 true and 25 fake news headlines with average partisanship ratings between 3.5 and 4. This resulted in a politically balanced (half Republican-leaning and half Democrat-leaning) but not too polarizing (close to the midpoint of a scale regarding political ideology) subset of 100 news items. From this subset, we removed two true news headlines, one for being outdated and the other for being ambiguously worded, and three fake news headlines, two for the same reasons as the true news headlines, and one for eliciting near-floor veracity ratings in Chen et al. (2023). We omitted source information from all items to prevent participants from relying on this feature as a shortcut to making decisions about the veracity of the items (e.g., rating items from mainstream news sources as *true* and unknown sources as *false*).

Design

This study was an observational study without an intervention. The independent variable was item type (true vs. fake). The two main dependent variables were participants' veracity ratings and the decision strategies they used to make each veracity rating. Age, gender, and political orientation were measured as demographic variables since previous studies have found them to influence true and fake news discrimination (Calvillo et al., 2020; Calvillo et al., 2021a; Modirrousta-Galian et al., 2023).

Procedure

Device restrictions were applied on Prolific, which suggested that participants access the experiment through a computer. Since this was a remote online study, participants could use any web browser or computer of their choosing.

Participants were first shown a combined information sheet and consent form. To indicate that they had read the form and agreed to provide informed consent, participants clicked a button at the bottom of the web page. After this, they automatically entered full screen mode and were shown the following warning: “To minimize distractions, you have now entered full screen mode. Please do not exit full screen mode unless absolutely necessary. If you exit full screen mode too many times, we will not be able to use your data for our study”. If a participant exited full screen mode, they automatically re-entered full screen mode whenever they pressed the “next” button. Participants were then asked for their Prolific IDs, which they provided by typing or pasting it into a textbox.

Subsequently, participants were shown the following instructions:

You'll now be presented with different news headlines, all of which have been reported on the internet by various sources. For each headline, we'd like you to indicate the extent to which you believe they contain true or false information. We'd also like you to indicate what decision strategy you used to make these judgements.

There will be five decision strategies for you to pick from:

- *Guess - your response was based on nothing but a pure guess.*
- *Intuition - your response was based on a feeling or a hunch such that you had some confidence but could not explain why.*
- *Rule - your response was based on one or more rules and the nature of those rules could be stated if asked.*
- *Familiarity - your response was based on feelings of familiarity due to having seen or heard about this news item before.*
- *Prior knowledge - your response was based on pre-existing knowledge about the general topic presented in this news item.*
- *Other.*

Guess, intuition, and familiarity are self-explanatory.

To provide an example of a rule, consider a hypothetical scenario where true news headlines are usually italicized while false news headlines are usually underlined. If you were to come across an italicized news headline, you'd likely label it as false because of the rule that false news headlines are usually italicized while true news headlines are usually underlined.

To provide an example of prior knowledge, consider a news headline that states "there are clouds in the sky". You know that there are clouds in the sky, so you'd likely label this news headline as true because of your pre-existing knowledge about clouds in the sky.

If you feel as though you did not use any of the defined decisions strategies, please select "Other".

Click the → button when you're ready to begin.

Participants then rated the veracity of 40 news headlines (20 true and 20 fake randomly selected for each participant from the set of 95 headlines) on a 6-point Likert scale (1 = *high confidence false*, 2 = *medium confidence false*, 3 = *low confidence false*, 4 = *low confidence true*, 5 = *medium confidence true*, 6 = *high confidence true*). After each veracity rating, participants selected one of the five decision strategies, which were presented in a list. The order of all the decision strategies apart from *other*, which was always last, was randomized for each question.

Next, participants were asked for their age, gender, and political orientation. To enter their age, participants typed their answers into a textbox. To indicate their gender, participants chose between four options: *male*, *female*, *other*, and *prefer not to say*. To specify their political orientation, participants rated themselves on a 7-point Likert scale that ranged from 1 (*very left-wing*) to 7 (*very right-wing*). Finally, participants received a written debriefing. This study took approximately 13 minutes to complete but, since progression was entirely self-paced, the completion time varied between participants.

Pilot Studies

This current study built on two earlier pilot studies. All data, analytic code, and materials needed to replicate the two pilot studies, as well as a description of their method and results, are available on OSF (https://osf.io/qfe3g/). The first pilot study differed from the current study in five aspects. First, participants were given less guidance before the rating task. Second, participants were asked to rate half as many news headlines. Third, the decision strategies were always listed in the same order, specifically *guess*, *intuition*, *rule*, *familiarity*, *prior knowledge*, and *other*. Therefore, participants may have chosen *guess* and *intuition* most frequently because they were always placed first in the list. Fourth, participants were asked to elaborate on what *rule*, *prior knowledge*, or *other* decision strategy they used by typing their answer into a textbox. Therefore, participants may have chosen those options least because they required elaboration. Lastly, the first pilot study was not preregistered. The second pilot study addressed the limitations of the first pilot study and was thus identical to the current study apart from having a considerably smaller sample size (N = 60 in both the first and second pilot studies). The following three key results remained consistent across the two pilot studies and the current study: (a) participants predominantly chose decision strategies indicative of tacit rather than explicit knowledge; (b) the guessing criterion was present; and (c) participants displayed a conservative response bias for all decision strategies apart from *familiarity*, for which they showed a slightly liberal response bias.

Results

Frequency Analysis

The raw and relative frequencies with which participants chose the different decision strategies to discriminate news items are shown in Table 2. A McNemar's Chi-squared test showed that the pooled relative frequency of the *guess* and *intuition* responses was significantly greater than the pooled relative frequency of the *rule* and *prior knowledge* responses, $\chi^2(1, N = 327) = 4808$, $p < .001$, $g = .21$. Indeed, participants were three times more likely to report using decision strategies indicative of tacit knowledge (.63) than explicit knowledge (.21).

Table 2

Raw and Relative Frequency of Each Decision Strategy

Decision strategy	All news items		True news items		Fake news items	
	Raw Frequency	Relative frequency	Raw Frequency	Relative frequency	Raw Frequency	Relative frequency
Guess	4742	.36	2,568	.39	2,174	.33
Intuition	3530	.27	1,626	.25	1,904	.29
Familiarity	1932	.15	1,178	.18	754	.12
Prior knowledge	1929	.15	843	.13	1,086	.17
Rule	735	.06	246	.04	489	.07
Other	212	.02	79	.01	133	.02
Guess & intuition	8,272	.63	4,194	.64	4,078	.62
Rule & prior knowledge	2,664	.21	1,089	.17	1,575	.24

Note. The bottom two rows show the raw and relative frequencies of the decision strategies indicative of tacit knowledge (*guess* and *intuition*) and explicit knowledge (*rule* and *prior knowledge*).

Receiver Operating Characteristic (ROC) Analysis

Receiver operating characteristic (ROC) analysis allows for discrimination and response bias to be measured separately (Higham & Higham, 2019). In the context of our study, discrimination refers to the ability to distinguish between true and fake news, while response bias refers to the overall tendency to rate all news as *true* or *false*. To separate these two distinct aspects of performance, we conducted ROC analysis on the veracity ratings, both separately for each decision strategy and collapsed over all decision strategies. We preregistered that at least 54 participants needed to make veracity ratings for at least one true news item and one fake news item with a given decision strategy for it to be analyzed individually with ROC analysis. This minimum data requirement was necessary to assess participants' discrimination and response bias. The sample size was based on an a priori power analysis in G*Power 3.1 that indicated 54 participants were required to detect a medium effect size with a two-tailed one-sample t-test ($n \approx 54$, $d = 0.50$, $1 - \beta = .95$, $\alpha = .05$).

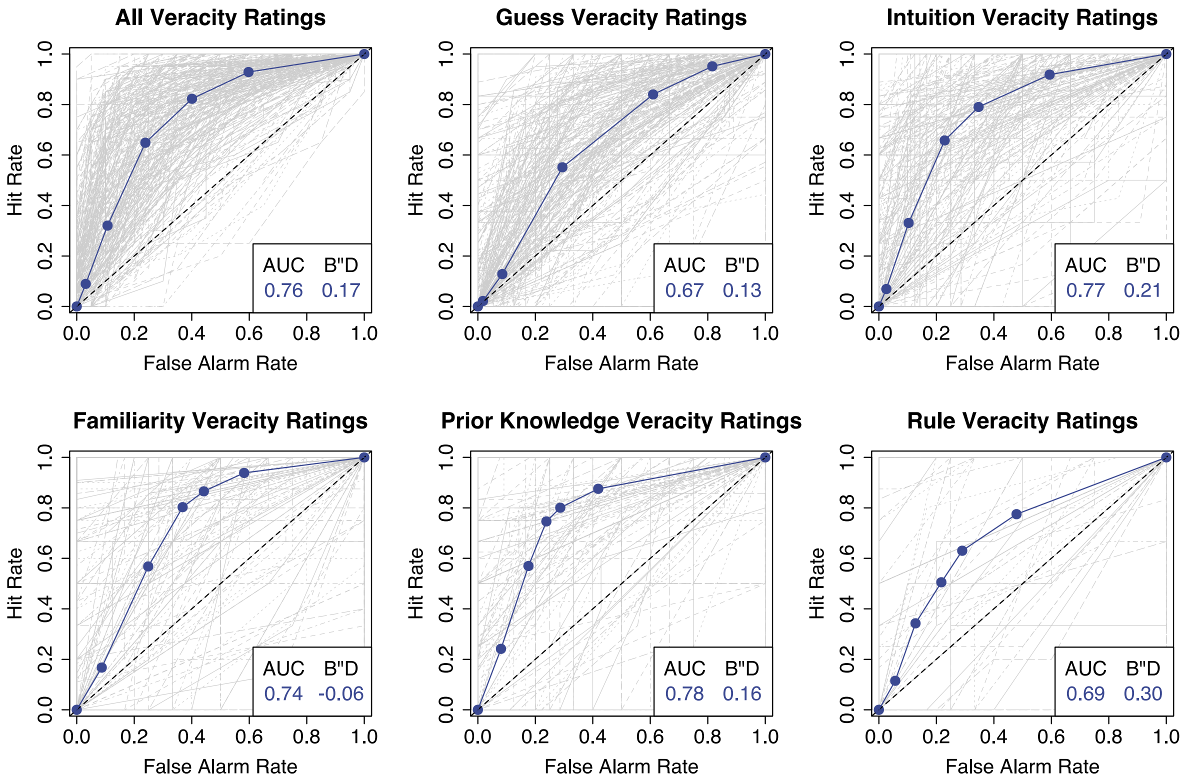
ROC curves are useful for visualizing discrimination and response bias. Chance-level discrimination is used as a reference point and corresponds to the straight diagonal line drawn from the bottom-left corner to the top-right corner of the ROC space. The further the ROC curve bows away from the diagonal towards the top-left portion of the ROC space, the better the discrimination. ROC points that cluster towards the bottom-left versus top-right portion of the ROC curve represent conservative (overall tendency to rate all news as *false*) versus liberal (overall tendency to rate all news as *true*) response biases, respectively.

For each participant, we calculated the area under the curve (AUC; a measure of discrimination) using the trapezoidal rule (Pollack & Hsieh, 1969), as well as *B″D* (a measure of response bias; Donaldson, 1992) for each point on the ROC curve. The AUC ranges from 0 to 1, with .50 representing chance-level discrimination and 1 representing perfect discrimination. *B″D* ranges from −1 to 1, with −1 representing an extreme liberal response bias, 0 representing no response bias, and 1 representing an extreme conservative response bias. We conducted one-sample *t*-tests to compare the mean AUC values to a theoretical mean of .50 (chance-level discrimination) and the mean *B″D* values (collapsed over ROC points) to a theoretical mean of 0 (no response bias). For a detailed discussion on signal detection theory (SDT), ROC analysis, AUC, *B″D*, and why these methods and measures are optimal for fake news research, see Modirrousta-Galian and Higham (2023).

All decision strategies apart from *other* met the minimum data requirement to be analyzed individually. The ROC curves (both for individual participants and aggregated across participants) as well as the mean AUC and *B″D* values for veracity ratings are shown in Figure 1. The ROCs in Figure 1 were computed both for the data pooled across all decision strategies and for data separated by decision strategy (apart from *other*). The results of the one-sample *t*-tests are shown in Table 3. In summary, participants discriminated between true and fake news significantly above chance-level in the pooled data and also separately for each decision strategy, even when they reported that they were guessing. Furthermore, participants showed a conservative response bias in all cases except when they chose the *familiarity* decision strategy, for which they showed a slightly liberal response bias. For scatterplots showing each participants' AUC and *B"D* values for the data pooled across all decision strategies and for data separated by each decision strategy (apart from *other*), see Figures S1 and S2 in the Supplemental Material.

Figure 1

ROC Curves for All Veracity Ratings and for Veracity Ratings Conditioned on Each Decision Strategy



Note. ROC = receiver operating characteristic. The faint grey lines in each plot represent the ROC curves for each participant.

Table 3

One-Sample t-Tests Comparing Observed Means Against Theoretical Means

Veracity ratings	*t*	*df*	*p*	*d*	BF_{10}
AUC					
All	37.17	326	< .001	2.06	2.55×10^{115}
Guess	15.26	307	< .001	0.87	1.41×10^{36}
Intuition	23.73	299	< .001	1.37	1.35×10^{67}
Familiarity	13.88	231	< .001	0.91	9.77×10^{28}
Prior knowledge	16.97	228	< .001	1.12	8.59×10^{38}
Rule	6.17	88	< .001	0.65	568,425.30
B"D					
All	10.68	326	< .001	0.59	7.22×10^{19}
Guess	9.00	307	< .001	0.51	1.94×10^{14}
Intuition	10.51	299	< .001	0.61	1.11×10^{19}
Familiarity	-2.33	231	.021	0.15	1.03
Prior knowledge	5.40	228	< .001	0.36	56,276.36
Rule	6.20	88	< .001	0.66	661,595.50

Note. AUC = area under the curve. BF_{10} = the Bayes factor that quantifies the empirical evidence in favor of the alternative hypothesis. The one-sample *t*-tests on AUC values compared the AUC values to a theoretical mean of .50 (chance-level discrimination). The one-sample *t*-tests on *B"D* values compared the *B"D* values to a theoretical mean of 0 (no response bias).

Linear Mixed-Effects Models

The ROC analysis reported above collapsed participants' ratings over news headlines to produce one AUC value and one *B"D* value for each participant. That analysis therefore accounted for subject- but not item-level variability. There are often important sources of variation between items, as is the case with news headlines. For example, our news headlines covered a vast range of topics and were accompanied by unique photographs, both of which could affect perceptions of veracity. Consequently, to assess participants' discrimination while accounting for both subject- and item-level variability, and to examine demographic effects, we ran linear mixed-effects models in R (Version 4.2.3) with the lme4 package (Version 1.1.32; Bates et al., 2015).

We did not have strong predictions for the fixed effects, so we adopted an exploratory model-building strategy to obtain the best-fitting and most parsimonious model.[1] We once again analyzed the data both separately for each decision strategy and collapsed over all decision strategies. To keep the subgroup analyses consistent, we again preregistered that at least 54 participants needed to make veracity ratings for at least one true news item and one fake news item with a given decision strategy for it to be analyzed independently with linear mixed-effects models. We used a step-up strategy to build the fixed effects structure first and the random effects structure second, and then planned to use a step-down strategy to trim the fixed-effects structure (for more information on step-up and step-down strategies, see Martínez-Huertas et al., 2022; Ryoo, 2011; Thrane et al., 2018; West et al., 2007). We started with an intercept-only model that included veracity ratings as the dependent variable, item type (true vs. fake) as the fixed effect, and participant number and item number as random effects. Then, we forward fitted the model by adding terms individually. We tested whether the addition of terms significantly increased the model fit with likelihood ratio tests. Following Pinheiro and Bates (2000) and Yan et al. (2014), we used maximum likelihood estimates when comparing models with different fixed effects structures, and restricted maximum likelihood estimates when comparing models with different random effects structures. Terms that significantly improved the model fit ($p < .05$) without introducing convergence issues were retained. For a step-by-step explanation on how we did this analysis, see Method Supplement S1 in the Supplemental Material.

The results from the final linear mixed-effects models (see Table 4) are in accordance with the results from the ROC analysis. Specifically, participants' veracity ratings for true news items were significantly higher than their veracity ratings for fake news items, which

[1] The preregistered analysis plan for the linear mixed-effects model analysis suggested running intercept-only models. We ran random-slope models instead since they have a lower rate of false positives (Barr et al., 2013). Furthermore, the preregistered analysis plan suggested examining the effects of age, gender, and political orientation by including them as fixed effects in the linear mixed-effects models. Although our exploratory model-building strategy follows this plan, for the sake of transparency, we affirm that it was not our original approach. Initially, we included age, gender, and political orientation separately as fixed effects, which led to a total of 24 models. To make the analysis more parsimonious and to again reduce the rate of false positives, we adopted the exploratory model-building strategy outlined in the main text, which led to a total of six models.

indicates above-chance discrimination. This was the case in the pooled data and for the data separated by decision strategy, even when participants reported that they were guessing. In terms of demographic effects, the older the participant, the better their discrimination across all data as well as for intuition data. Furthermore, the more right-wing the participant, the worse their discrimination across all data as well as for intuition, familiarity, and prior knowledge data.

Table 4

Results From the Final Linear Mixed-Effects Models

Fixed effects	*b*	*SE*	*t*	*df*	*p*
Model 1 (all data)					
Intercept	2.38	0.09	27.24	126.08	< .001
type [true]	1.42	0.12	12.02	109.37	< .001
political orientation	0.13	0.03	4.71	290.98	< .001
age	−0.01	0.00	−4.92	323.81	< .001
type [true] × political orientation	−0.14	0.03	−4.01	206.38	< .001
type [true] × age	0.02	0.00	5.72	323.39	< .001
Model 2 (guess data)					
Intercept	2.77	0.06	45.34	158.81	< .001
type [true]	0.74	0.08	9.59	111.16	< .001
Model 3 (intuition data)					
Intercept	2.40	0.10	24.31	164.36	< .001
type [true]	1.46	0.12	11.73	111.92	< .001
political orientation	0.12	0.03	3.59	200.93	< .001
age	−0.02	0.00	−4.27	257.65	< .001
gender [male]	−0.20	0.07	−2.94	260.85	.004
gender [other]	−0.14	0.25	−0.57	331.28	.567
gender [prefer not to say]	0.12	0.54	0.22	192.86	.828
type [true] × political orientation	−0.08	0.04	−1.93	144.35	.056
type [true] × age	0.01	0.00	3.33	254.18	.001
Model 4 (familiarity data)					
Intercept	2.71	0.12	23.40	157.62	< .001
type [true]	1.53	0.15	10.21	120.42	< .001
political orientation	0.21	0.06	3.79	154.62	< .001
type [true] × political orientation	−0.23	0.07	−3.36	114.80	.001
Model 5 (prior knowledge data)					
Intercept	2.23	0.13	16.72	127.75	< .001
type [true]	1.88	0.18	10.23	118.38	< .001
political orientation	0.20	0.05	4.09	152.89	< .001
type [true] × political orientation	−0.17	0.06	−2.63	131.24	.010
Model 6 (rule data)					
Intercept	2.14	0.14	15.09	100.60	< .001
type [true]	1.25	0.19	6.56	92.07	< .001

Note. Seven participants chose *other* and one chose *prefer not to say* when asked to indicate their gender. Therefore, the main effects of gender for the *other* and *prefer not to say* categories should be interpreted with caution. To minimize the issue of small subgroups within the age and political orientation variables, we coded them as continuous variables.

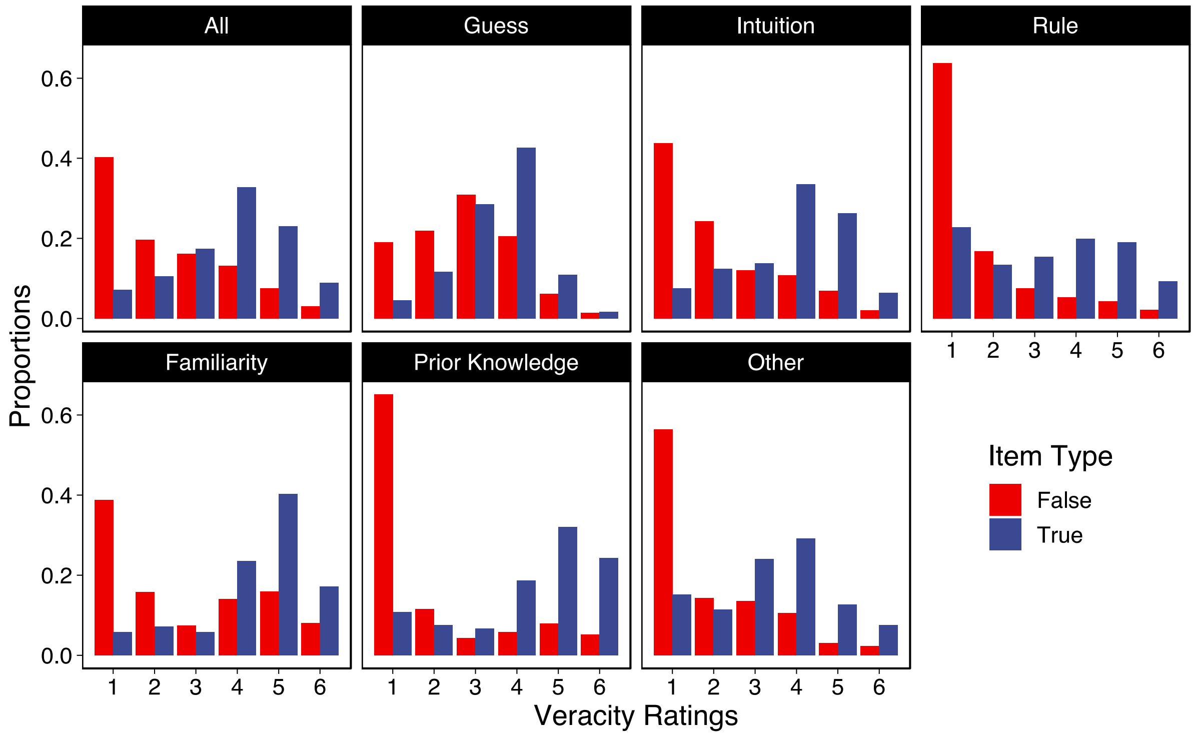
Item Analysis

To determine the specific patterns of responding that led to the discrimination and response bias effects revealed through ROC and linear mixed-effects model analyses, we examined the proportion of true and fake news items that were assigned each veracity rating, split by decision strategy (see Figure 2). Generally, participants' veracity ratings clustered towards the lower limit of the scale for fake news items (76% of fake news items were given veracity ratings of 1, 2, or 3) and towards the upper limit of the scale for true news items (65% of true news items were given veracity ratings of 4, 5, or 6), which explains their above-chance discrimination. Interestingly, this clustering was stronger for the fake news items, indicating that participants were better at correctly classifying fake news items than true news items.

When participants reported that they were guessing, their veracity ratings clustered towards the middle of the scale for both true and fake news items (61% of news items were given veracity ratings of 3 or 4 when participants were guessing, compared to 35%, 25%, 18%, 24%, and 39% when using intuition, familiarity, prior knowledge, rule, and other, respectively). This result makes intuitive sense; when participants believed that they were guessing and therefore less confident in their answers, they tended to choose *low confidence false* or *low confidence true* veracity ratings. Nevertheless, even when guessing, participants tended to choose *low confidence true* veracity ratings for true news items (29% and 43% of true news items were given veracity ratings of 3 and 4, respectively, when participants were guessing) and *low confidence false* veracity ratings for fake news items (31% and 21% of fake news items were given veracity ratings of 3 and 4, respectively, when participants were guessing), which explains their above-chance discrimination when guessing. For line graphs showing the relative frequency of each decision strategy per true and fake news item, see Figures S3 and S4 in the Supplemental Material.

Figure 2

The Proportion of True and Fake News Items Assigned Each Veracity Rating, Split by Decision Strategy



Note. Veracity ratings were made on a 6-point Likert scale (1 = *high confidence false*, 2 = *medium confidence false*, 3 = *low confidence false*, 4 = *low confidence true*, 5 = *medium confidence true*, 6 = *high confidence true*).

Discussion

In this preregistered study, we applied the self-report method of measuring tacit and explicit knowledge typically used in implicit learning experiments (Dienes & Scott, 2005; Neil & Higham, 2012; Scott & Dienes, 2008; Ziori et al., 2014) to a true and fake news discrimination task. Specifically, we asked participants to rate the veracity of different news headlines and indicate what decision strategy they used to make each rating. Participants predominantly chose the *guess* and *intuition* decision strategies, which are indicative of tacit knowledge (Dienes & Scott, 2005; Scott & Dienes, 2008; Ziori et al., 2014). Furthermore, participants showed above-chance discrimination when veracity ratings were pooled across all decision strategies, and also when veracity ratings were examined separately for each decision strategy. This is particularly interesting for the *guess* decision strategy; participants had the necessary knowledge to discern the veracity of news headlines, as indicated by their above-chance performance, but did not articulate this, as indicated by their self-reported guessing. This pattern of responding is called the guessing criterion and is also indicative of tacit knowledge (Dienes, 2007).

The finding that tacit knowledge forms the dominant basis of true and fake news discrimination has important implications for interventions aimed at improving this skill. For example, interventions that aim to improve true and fake news discrimination by teaching people explicit rules, a dominant approach in the literature, may not be successful. Indeed, several interventions that provide explicit guidance for identifying fake news have been shown to decrease belief in both true and fake news (Clayton et al., 2020; Modirrousta-Galian & Higham, 2023; Rędzio et al., 2023), suggesting that they only affect response bias. This is concerning since decreased belief in true news can have potentially harmful consequences, such as vaccine hesitancy (Dubé et al., 2013). Critically, some research has found that attempts to enhance learning with explicit instructions or rules can interfere with learning when the knowledge is tacit, as shown in the context of motor skill learning (Boyd & Winstein, 2003; Boyd & Winstein, 2004; Boyd & Winstein, 2006; Green & Flowers, 1991), artificial grammar learning (Reber, 1976), and sequence learning (Curran & Keele, 1993). Consequently, to develop effective interventions for improving true and fake news discrimination, we recommend researchers draw inspiration from methods that improve the tacit knowledge we use in everyday life, such as for languages, music, and motor skills (e.g., mentorship and repeated practice; Dienes & Scott, 2005; Edmondson et al., 2003). However, this is simply a recommendation; the results from this study do not provide direct evidence for the types of interventions that will be successful in improving true and fake news discrimination, but they may be useful in pointing us in the right direction.

Relatedly, it may not be that explicit instruction as a whole is inadequate for improving true and fake news discrimination, but rather that much of the specific explicit instruction provided thus far is inadequate. Perhaps a combination of tacit and explicit training is required. Consistent with this possibility, Brodsky et al. (2021) found that the online SIFT curriculum (Stop, Investigate the source, Find better coverage, and Trace claims; Caulfield, 2019), which incorporates direct instruction and repeated practice, improved students' fact-checking. Fact-checking can be considered a precursor to true and fake news discrimination (Brodsky et al., 2021), so incorporating both tacit and explicit training may improve the latter as well as the former.

We also found that participants displayed a conservative response bias (overall tendency to rate all news as *false*) when veracity ratings were pooled across all decision strategies, and for most decision strategies when analyzed separately. The exception was *familiarity*, which instead showed a slightly liberal response bias (overall tendency to rate all news as *true*). This result is interesting when considered in the context of the illusory truth effect, which refers to the finding that repeated exposure to information increases its perceived truth, regardless of its objective veracity (Henderson et al., 2022). Indeed, Ecker et al. (2022) reasoned that the illusory truth effect can arise from familiarity cues. Finally, we found that, generally, older participants showed better discrimination, and more right-wing participants showed worse discrimination. The effect of political orientation is consistent with the literature (Calvillo et al., 2020; Calvillo et al., 2021a; Garrett & Bond, 2021; Gupta et al., 2023; Modirrousta-Galian et al., 2023), whereas the effect of age is consistent with some studies (Calvillo et al., 2020; Gupta et al., 2023) but not others (Modirrousta-Galian et al., 2023). These mixed results can be attributed to the fact that demographic differences are largely item- and sample-specific and should be considered within the particular methodological context in which they occur (Calvillo et al., 2020; Calvillo et al., 2021b; Halpern et al., 2019). Although the demographic results should therefore be interpreted with caution, we reported them in case they are of interest to researchers that aim to target specific groups with interventions.

Our study had several design-related limitations. First, participants may have used both tacit and explicit knowledge and thus more than one decision strategy to make a judgement (Ellis & Roever, 2021; Rebuschat, 2013). However, the self-report procedure only allowed participants to choose one decision strategy per veracity rating. Nevertheless, this procedure presumably led participants to choose the decision strategy that was most influential on their judgement, which was our main objective. Another limitation is that the reported decision strategy may not have always been the one that participants actually used. This may have been due to participants being unable to accurately introspect about their cognitive processes, or the presence of cognitive biases that made some decision strategies easier to report than others. Although this validity issue applies to all self-report methods (Dienes, 2007), we attempted to mitigate it by examining participants' veracity ratings and decision strategies together. This allowed us to determine whether these two responses were in accordance with each other and therefore valid, which we found to be the case. For example, when participants reported that they were guessing (and therefore less confident in their answers), their veracity ratings clustered towards the middle of the scale (*low confidence false* and *low confidence true*) for both true and fake news items.

Furthermore, the rating task is not representative of how people typically engage with news headlines. Therefore, the factors affecting discrimination and response bias in our study may have been different from those at play when people encounter news headlines in everyday life. Lastly, although the study was conducted in March 2023, most of its news headlines were from 2022, and perceptions of past versus current news headlines may differ. It is difficult to overcome this issue when using real news headlines found online because news quickly becomes obsolete, regardless of whether researchers collect and pretest news items themselves or use pretested ones from a recent paper.

Overall, we found that participants discriminated well between true and fake news without any training. Moreover, tacit knowledge formed the dominant basis of this discriminative ability, whereas explicit knowledge played a comparatively minor role. This finding has important implications for interventions that aim to improve people's ability to detect false information and thus tell it apart from credible information. Specifically, giving people explicit guidance for this purpose may be counterproductive, which might explain why some of the interventions that adopted this approach have had limited success. Therefore, to develop effective interventions, we recommend applying the techniques used to improve our tacit knowledge in everyday life, such as when learning a new language, instrument, or sport.

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