Expectation management in humans and LLMs

Benjamin Menashe[1], Austin Drake[2], Michal Ben-Shachar[1]*

[1]The Gonda Multidisciplinary Brain Research Center, Bar-Ilan University, Ramat-Gan, Israel
[2]Department of Psychology, University of Jyväskylä, Jyväskylä, Finland

*Corresponding author: menashb@biu.ac.il

Abstract

Mirative markers, such as “surprisingly”, explicitly encode a violation of expectations. Such markers are used for expectation management during communication. Sensitivity to mirative markers relies on two abilities: i) updating expectations upon recognizing a mirative marker, and ii) identifying expectation violations warranting the use of a mirative marker. In this study we compared sensitivity to mirative markers in humans and large language models (LLMs). In part 1, we used a sentence-completion task, where humans and LLMs were presented with sentence fragments and asked to continue them. Results show that for both humans and LLMs, the presence of a mirative marker significantly increased response entropy and decreased top response probability, in line with theoretical proposals for mirative markers. In part 2, we created a novel task of mirative polarity selection where humans and LLMs are presented with a sentence pair and asked to select whether it was connected by a mirative marker (“surprisingly”) or an anti-mirative marker (“unsurprisingly”). Results show that LLMs perform at an impressive human level. We conclude that both humans and LLMs use mirative markers as cues for calibrating their subsequent expectations during sentence processing.

Intro

Humans constantly form expectations about upcoming stimuli[1,2]. Linguistic stimuli are of no exception: it is well-demonstrated that humans use context and prior knowledge to form expectations and predictions about upcoming linguistic information, and then test those predictions against the actual incoming input[3–5]. Encountering a semantic violation of expectations is associated with longer processing time[6–10], an elevated amplitude of the N400 ERP component[11–14], and neural activation across many brain regions[15–19]. These results are in line with “predictive processing” theories of the brain, whereby such violations of expectations are regarded as “prediction errors” which the brain aims to minimize[20–23].

In natural discourse, speakers often attempt to explicitly manage their interlocutors' expectations by using mirative markers. *Mirative markers* are linguistic elements that encode violation of expectations[24–26], including words such as “surprisingly” and “remarkably”. Mirative markers are widely used by speakers to inform their interlocutors about an upcoming unexpected message. In theory, such expectation management helps interlocutors avoid “prediction errors” and the associated increase in processing time and difficulty incurred by such errors. In this paper, we aim to study expectation management using mirative markers, in humans and in large language models (LLMs). The aim of this

study is to quantify and compare sensitivity to mirative markers, which relies on two abilities: i) updating expectations upon recognizing a mirative marker, and ii) identifying expectation violations warranting the use of a mirative marker. The extent to which expectation management is successful depends on the sensitivity to mirativity of both the speaker and interlocutor.

Mirativity is considered to be a language-universal category[24]. Mirativity can be marked using words (e.g., “surprisingly”), exclamatory particles or intonation (e.g., “Wow!”), and even morphological affixes in certain languages[27]. Conversely, a confirmation of expectations can also be marked using words such as “unsurprisingly” and “expectedly”, which we refer to as *anti-mirative markers*. According to linguistic theory, mirative markers are appropriate only there exists a more expected proposition that is false[28]. This implies that mirative markers should modify expectations in the following way: decrease the probability for the most-expected upcoming stimuli, and increase it for lesser-expected upcoming stimuli. Such a process is referred to as *domain widening*, whereby the domain of plausible upcoming stimuli is expanded to include lesser-expected stimuli[29,30]. This is effectively equivalent to an increase in the entropy of the expectation distribution. Entropy is a quantitative measure of uncertainty taken directly from information theory[31], and its effects on human behavior and neural activity have been extensively researched[32–36].

Two previous studies which addressed the neural effects of expectation-disconfirming markers, both using ERPs, have presented conflicting results. In the first study[37], participants read scenarios containing unexpected target words. On half the trials, the target word was preceded by the discourse marker "even so", which is assumed to reverse readers’ expectations. Results showed that the presence of “even-so” attenuated the amplitude of the N400 component for the otherwise unexpected target words. In a later study[38], participants read dialogues in Dutch with unexpected endings. On half the trials the ending was preceded by discourse marker “eigenlijk” (“actually”), which signals expectation-disconfirmation. Results showed no evidence for a main effect of discourse marker or interaction of discourse marker and predictability on the N400 amplitude. As such, there is currently only limited and conflicting empirical evidence on processing mirative markers and subsequent expectation modification.

In recent years, LLMs have revolutionized the field of natural language processing. In essence, LLMs are trained to predict the next token given a sequence of text, based on exposure to enormous corpora of language[39–42]. Post training, an LLM takes a sequence of text as input and provides a probability estimate for each token (in its vocabulary) to be the next token in the sequence. This has been compared to forming expectations in humans, in what has been called a “shared computational principle of language

comprehension”[43]. LLMs have been used to gain insight into human behavior[44,45], and neural activity[46–48]. While state-of-the-art LLMs have shown impressive performance on various tasks and benchmarks, it is yet unclear how LLMs explicitly manage expectations or respond to expectation management markers, if at all.

In this study, we measured human participants and LLMs on their sensitivity to mirativity. In part 1, we studied how mirative markers modify expectations. We used a sentence-completion task, where human participants and LLMs were presented with sentence fragments and asked to continue them. We manipulated the sentences to begin either with a mirative marker or a neutral marker, and compared the respective responses. In part 2, we studied if LLMs identify violations of expectations to the same level as human participants do. We created a novel task called *mirative polarity selection* where human participants and LLMs are presented with a sentence pair and asked to select whether it was connected by a mirative marker or by an anti-mirative marker.

Results

Part 1: Increased entropy in response to mirative markers

Using a sentence-completion task, we tested how the presence of a mirative marker (“surprisingly”) in the beginning of a sentence fragment affects expectations about upcoming words as compared to a neutral marker (“yesterday”). We tested human participants using an online questionnaire containing thirty novel sentence fragments were presented. We then tested the meta-llama-3/3.1/3.2 series of LLMs on the same sentence fragments. Since a mirative marker indicates an upcoming violation of expectations, we predicted that it will lead to a decrease in the probability of the most-expected response and to a general increase in the probability of lesser-expected responses, leading to an overall increase in the entropy of expected responses.

We found that, in human participants, the inclusion of a mirative marker in the beginning of a sentence fragment resulted in a significant decrease in the probability of the most common response to the neutral marker ($t_{28} = -6.85$, $p<.001$, Fig. 1A), and a significant increase in the entropy of the response distributions ($t_{28} = 5.58$, $p<.001$, Fig. 1B). Similar to human participants, a significant decrease in probability for the top response to the neutral marker was found for all LLMs (see Supplementary Table 1 for the full statistics. See Fig. 1D for an example LLM). Moreover, the entropy of the response distribution increased for all LLMs, although this increase was significant in only three of the six LLMs

tested (Llama-3-8B, Llama-3.1-8B, Llama-3.2-3B. See Fig. 1E for an example LLM). A visual inspection of the top 10K tokens suggested that mirative markers decrease the probability of the top 10-20 tokens and increase the probability of the rest of the tokens (Fig. 1F). Taken together, this provides evidence that humans and LLMs process the mirative marker as an indicator for an upcoming violation of expectation, and both humans and LLMs modify their expectations accordingly.

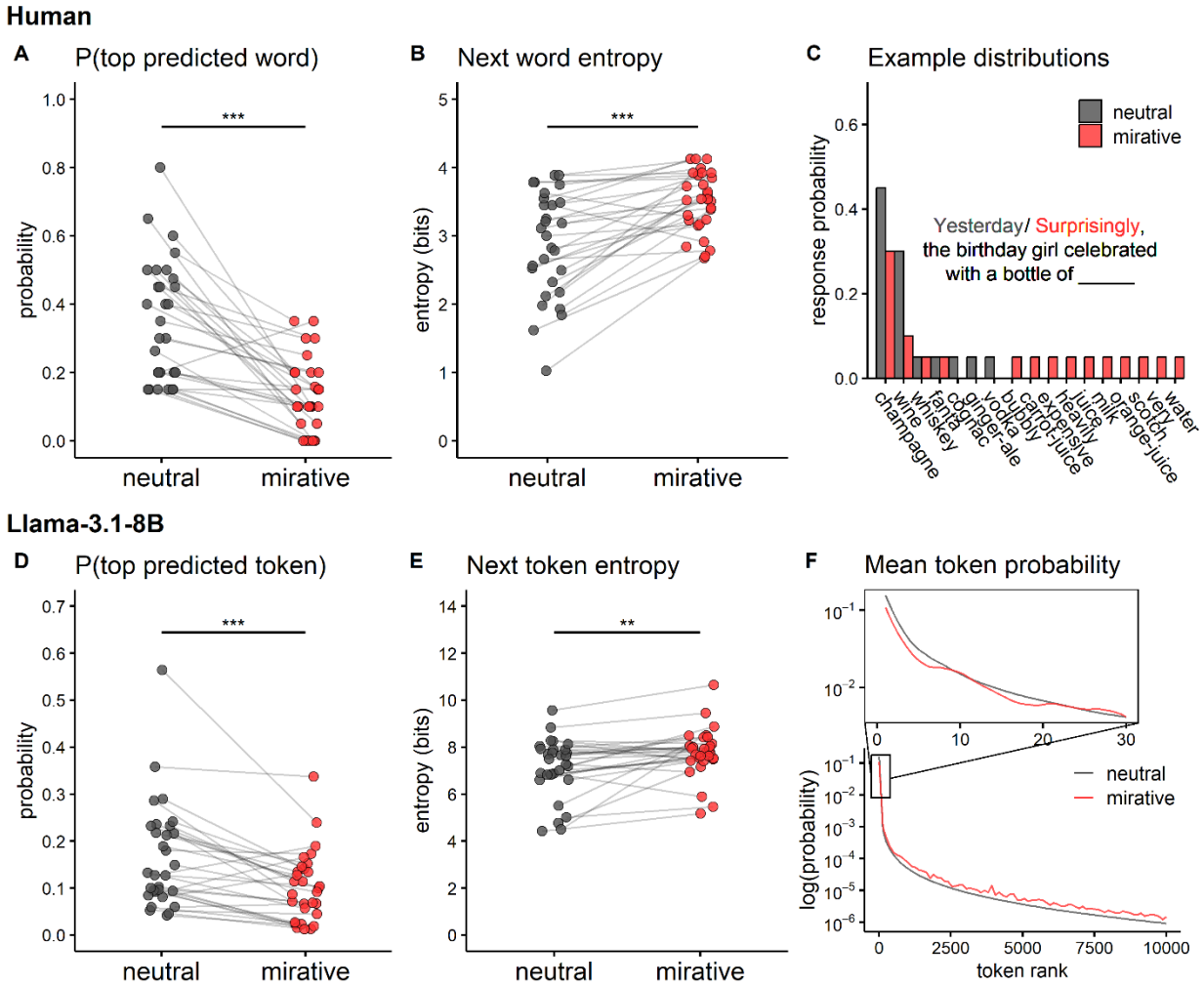

Figure 1. Mirative markers modify expectations. Top: *Human participants were presented with 30 sentence fragments and asked to continue them with the next word. Stimuli began either with a neutral marker ("yesterday") or a mirative marker ("surprisingly").* ***A)*** *Probability of the most common response in the neutral condition, and of the same response in the mirative condition. *** p<.001.* ***B)*** *Entropy over the response distribution, per condition. *** p<.001.* ***C)*** *Example of response distributions for the same sentence fragment ("the birthday girl celebrated with a bottle of ___") in the neutral condition in grey and in the mirative condition in red.* ***Bottom:*** *we used an LLM (meta-llama-3.1-8b) to generate next token predictions for the same 30 sentence fragments presented to human participants.* ***D)*** *Probability of the top token in the neutral condition, and of the same token in the mirative condition. The difference is significant even when removing the top outlier point. *** p<.001.* ***E)*** *Entropy over the next token distribution, per condition. ** p= .002.* ***F)*** *Mean probability by marker, calculated across all stimuli, for each of the top 10K tokens in the neutral condition. X-axis represents token rank, determined by descending probability in the neutral condition. Y-axis is in log-scale. Data points were smoothed using locally estimated scatterplot smoothing (LOESS) with span=10. The upper panel is a magnified view of the top 30 ranks.*

In a follow-up analysis, we generated 1,365 text fragments of varying lengths taken from the Provo corpus[49]. We defined a "window of altered expectations" as the location and range of the increased entropy due to the presence of a mirative marker. The window was found to extend up to 2 sentences ahead (Fig. 2A) and approximately 5-40 words ahead (Fig. 2B, see also Supplementary Table 2 for the full statistics). This suggests that mirative markers have a limited window in which the violation of expectations is anticipated to occur.

In a linear mixed-effects model predicting the increased entropy by the POS of the most-expected word, all POS showed a significant increase in entropy and no significant difference was found between content words and function words (t_{830} = 0.38, p=.705, Fig. 2C). Additionally, we wanted to check if mirative markers modify expectations differently for different levels of contextual constraint, measured by the entropy in the neutral condition. No correlation was found between the level of contextual constraint and the increase in entropy in the mirative condition (standardized correlation coefficient = −0.010, p=.774, Fig. 2D). This suggests that the addition of a mirative marker generally results in an increase of entropy, regardless of the level of contextual constraint. Importantly, this also shows that the increase in entropy is not due to regression to the mean.

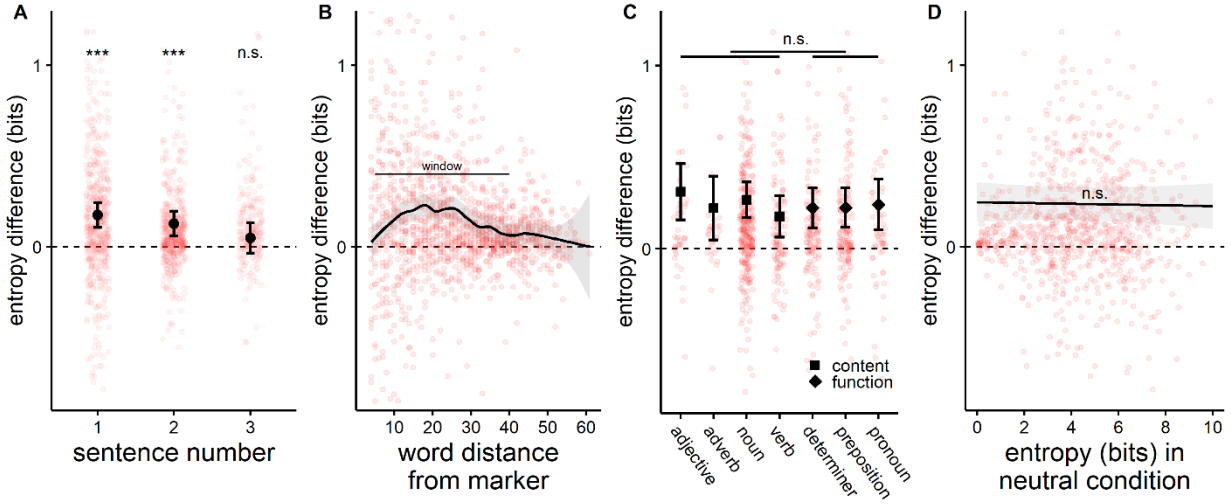

Figure 2. Mirative markers increase entropy. *We used an LLM (meta-llama-3.1-8B) to quantify the entropy following each word in 30 texts taken from the Provo corpus (Luke & Christianson, 2018). Texts began either neutrally, i.e., as they were in the corpus, or with a mirative marker ("surprisingly"). All plots show the difference in entropy between the mirative and the neutral condition, per word.* ***A)*** *Entropy difference per sentence number. Black points show the estimated means from a linear mixed-effects model per sentence number in the text. Errors bars show the 95% CI. Outliers above (n=51) and below (n=38) the y-axis limits are not shown but were included in the model. *** p<.001. n.s. not significant.* ***B)*** *Entropy difference per the word's distance from the mirative marker. Black line shows the locally estimated scatterplot smoothing (LOESS) with span=20 over the entropy difference of all words. Error regions show the 95% CI. Outliers above (n=51) and below (n=38) the y-axis limits are not shown but were included in the locally estimated scatterplot smoothing model.* ***C)*** *Entropy difference per the predicted token's part-of-speech. Only words which were in the first 2 sentences and within the mirative window (5 to 40 words) were used. Black points show the estimated means from a linear mixed-effects model per part-of-speech, with squares for content words and diamonds for function words. Errors bars show the 95% CI. Outliers above (n=26) and below (n=17) the y-axis limits are not*

shown but were included in the model. n.s. not significant. ***D)*** *Entropy difference per the entropy in the neutral condition. Black line shows the estimated trendline from a linear mixed-effects model. Error regions show the 95% CI. Outliers above (n=26) and below (n=17) the y-axis limits are not shown but were included in the model. n.s. not significant.*

Part 2: Identifying expectation violations

We tested human and LLM performance in identifying violations of expectation. For that, we devised a novel task called mirative polarity selection. Participants and LLMs were presented with a sentence pair and asked to select whether it was connected with a mirative marker ("surprisingly") or an anti-mirative marker ("unsurprisingly"). Sentence pairs were sampled from the Discovery dataset[50], and were originally connected by one of the markers in the corpus (this constitutes the correct response). We tested human participants using an online questionnaire, and we used the meta-llama-3/3.1/3.2-instruct series and the chatGPT-3.5/4/4o series of LLMs. We predicted that LLMs will perform near or at a human level, in line with their performance on theory-of-mind tasks[51].

Human mean accuracy on the mirative polarity selection task was 75.5% ± 1%. Participant performance varied widely (Fig. 3B), ranging between 46.7% (N=2) and 90% (N=3). This suggests high variability in the participants' ability to identify violations of expectations. Participant agreement on the responses was fair (percent agreement: 68.2%, Gwet's AC1: 0.376, $p<.001$). The relatively low level of mean accuracy and agreement may reflect the natural stimuli we used, as the sentence pairs may not have contained sufficient information for selecting the correct marker (see Supplementary Table 4 for examples with low human accuracy). Thus, we take the mean human accuracy and the top human accuracy as tentative benchmarks for estimated mean and top performance on this task.

LLM task performance varied, with some models approaching and some exceeding mean human performance (see Table 1 for the full statistics, and Fig. 3C for a comparison between human performance and selected LLMs). Within the meta-llama series, Llama-3-8B-Instruct and Llama-3.1-8B-Instruct performed well above chance but still below human level. The newer Llama-3.2 models both performed at chance level. This result may be due to their smaller number of parameters. Within the chatGPT series, GPT-3.5 performed above chance level but below human level, GPT-4 performed at human level, and GPT-4o performed above mean human level and near the top human level. GPT-4o-mini saw a drop in performance, which also may be due to its smaller number of parameters (see Table 1). A stricter measure of accuracy is the joint order accuracy, where LLM responses were considered correct only if they selected the correct label twice for a given sentence pair: once per each choice order presented. LLM performance as measured by joint order accuracy was lower than model accuracy for all

models, although many models still performed above chance level and GPT-4o still performed at an impressive mean human level (See Table 1 for the full statistics).

Table 2. Mirative polarity selection – summary of responses

model	mean accuracy	joint order accuracy	invalid responses	first choice presented	accuracy	mirative accuracy	anti-mirative accuracy	mirative response rate	anti-mirative response rate	mirative bias	order bias
Human	**75.5%** ± 1%			mirative	**74.9%** ± 2%	83.5% ± 2%	66.3% ± 4%	58.6% ± 2%	41.4% ± 2%	0.51 ± 0.3	−0.02 ± 0.1
				anti-mirative	**76.1%** ± 2%	81.6% ± 2%	70.5% ± 3%	55.6% ± 2%	44.4% ± 2%		
Llama-3-8B-Instruct	**65.2%**	40.4%	0.7%	mirative	**63.9%**	87.7%	40.2%	73.7%	26.3%	0.60 ± 0.1	−0.87 ± 0.1
				anti-mirative	**66.4%**	70.4%	62.4%	54.0%	46.0%		
Llama-3.1-8B-Instruct	**67.9%**	41.5%	1.8%	mirative	**65.7%**	88.0%	43.5%	72.3%	27.7%	0.31 ± 0.1	−1.43 ± 0.1
				anti-mirative	**70.0%**	60.8%	79.3%	40.9%	59.1%		
Llama-3.2-1B-Instruct	**47.4%**	24.6%	35.1%	mirative	**48.2%**	0.5%	99.7%	0.4%	99.6%	−14.4 ± 1.6	6.04 ± 1.6
				anti-mirative	**46.4%**	1.6%	97.8%	1.8%	98.2%		
Llama-3.2-3B-Instruct	**52.1%**	6.3%	0.5%	mirative	**54.3%**	12.6%	96.0%	8.3%	91.7%	1.56 ± 0.3	7.92 ± 0.5
				anti-mirative	**49.9%**	99.6%	0.4%	99.6%	0.4%		
GPT-3.5-turbo-0125	**61.3%**	26.4%	0.5%	mirative	**55.7%**	96.4%	14.6%	90.9%	9.1%	0.64 ± 0.1	−3.44 ± 0.2
				anti-mirative	**66.8%**	42.8%	91.0%	26.0%	74.0%		
GPT-4-0613	**76.9%**	62.8%	0.2%	mirative	**72.4%**	49.3%	95.4%	26.9%	73.1%	−1.06 ± 0.1	1.62 ± 0.2
				anti-mirative	**81.3%**	78.6%	84.0%	47.2%	52.8%		
GPT-4-turbo-2024-04-09	**78.5%**	61.7%	0.0%	mirative	**72.2%**	46.8%	97.6%	24.6%	75.4%	−0.88 ± 0.1	2.59 ± 0.2
				anti-mirative	**84.7%**	90.2%	79.2%	55.5%	44.5%		
GPT-4o-mini-2024-07-18	**68.7%**	48.3%	0.3%	mirative	**61.6%**	97.4%	25.7%	85.9%	14.1%	1.20 ± 0.1	−2.23 ± 0.2
				anti-mirative	**75.9%**	77.5%	74.3%	51.6%	48.4%		
GPT-4o-2024-08-06	**84.8%**	77.1%	0.0%	mirative	**84.3%**	87.0%	81.6%	52.7%	47.3%	0.12 ± 0.1	−0.32 ± 0.1
				anti-mirative	**85.2%**	84.6%	85.8%	49.4%	50.6%		

Mean ± SE where applicable.

Table 1. Mirative polarity selection – summary of responses. *Mirative polarity selection is a novel task where participants and LLMs are presented with a sentence pair and asked to select whether it was connected with a mirative marker ("surprisingly") or an anti-mirative marker ("unsurprisingly"). We used 1000 sentence pairs (500 per marker) from the Discovery dataset (Sileo et al., 2019). Human participants were presented with 60 randomly selected stimuli (30 per marker). Human participants and models were presented with stimuli where the choices were presented either mirative marker first or anti-mirative marker first. Mean accuracy is the mean accuracy over both choice orders. Joint order accuracy is the accuracy only if the model responded correctly for both choice orders. Invalid responses are the percent of response where the model did not respond with selecting a mirative or an anti-mirative marker. For every choice order, for human participants and for each model, we also report the accuracy, accuracy per correct marker (corresponding to true positive rate and false positive rate), and response rate per marker (corresponding to predicted positive rate and predicted negative rate). We then fit a logistic mixed-effects regression per model using the mirative response rate as the dependent variable, an intercept and choice order as the independent variables, and a random intercept per stimulus, in order to estimate the mirative marker bias and the order bias, respectively. Similarly, for the human participants we fit a logistic mixed effects regression with the same specification but with the addition of random intercepts per participant.*

To ensure that the high accuracy of the LLMs was derived from some ability to identify expectation violations and not due to some other variable, we measured the discriminability of the sentence pairs using several simple variables. Discriminability, measured using AUC, was very poor for most of the variables checked (second sentence length: 0.462, perplexity: 0.492, max surprisal: 0.546, similarity: 0.495, question: 0.508, negativity: 0.558), with the exception of the length of the first sentence where anti-mirative markers tended to be preceded by longer sentences as compared to mirative markers (AUC = 0.647, see Fig. 3D for the ROC of the various criteria). However, discriminability based on the length of the first sentence is still not sufficient to explain the performance of the better performing LLMs. Moreover, it was not a significant predictor of the LLM response beyond the stimulus label (using a logistic regression with a covariate for stimulus label, p>.42 for all LLMs). This supports the claim that LLMs succeed in mirative polarity selection due to some form of sensitivity to mirativity.

To further assess this claim, we tested LLM performance on manipulated versions of the stimuli: presenting just the first or just the second sentence of the pair. LLM performance decreased substantially in both conditions (Fig. 3E, see Supplementary Table 3 for the full statistics). This also suggests that LLM performance is not due to data contamination (where the model was trained on the stimuli and thus was "supervised" for the correct label). Following that, we presented LLMs with sentence pairs where the first and second sentence were randomly shuffled between pairs within the same label. The goal of this condition was to eliminate the semantic information between each pair of sentences, while preserving other global properties which might differ between labels. LLM performance decreased substantially on this condition as well (Fig. 3E, see Supplementary Table 3 for the full statistics). This shows that LLM performance is tied to the semantic information in the sentence pair, most likely the occurrence of an expectation violation (or confirmation). Thus, altogether, results from the manipulated stimuli conditions support the claim that LLMs succeed in the original task due to some form of sensitivity to mirativity and not due to data contamination or sensitivity to other properties of the stimuli.

Participants tended to select the mirative marker slightly more than the anti-mirative marker, although this difference was not significant ($p=.055$). Of the LLMs which performed above chance level, different tendencies were observed: Llama-3-8B-Instruct and Llama-3.1-8B-Instruct displayed a significant bias to select the mirative marker ($p<.001$, but it was of a similar magnitude to humans), GPT-4o was not significantly biased towards any label ($p=.378$), and GPT-4 had a significant bias to select the anti-mirative marker ($p<.001$, Fig. 4F, see Table 1 for the coefficient values). This suggests that while LLM performance can reach or exceed human level, it does not necessarily do so in a similar way to humans. Importantly, the mirative marker "surprisingly" is an order of magnitude more frequent than the anti-mirative marker "unsurprisingly" in natural corpora (using the *wordfreq* python library[52]: "surprisingly" Zipf frequency = 4.09, "unsurprisingly" Zipf frequency = 3.01, frequency ratio = 12.02), which means that some mirative bias may be expected if the base frequency of the markers is taken into account when selecting the markers.

Finally, LLMs also differed from human participants by their sensitivity to the order of the choices presented (Fig. 4G, see Table 1 for the coefficient values). In humans, no significant effect of order was found when estimating using all human participants ($p=.880$) or when only using the subset of participants who responded to both orders (coefficient = 0.10 ± 0.2, $p=.513$). However, all LLMs displayed a significant order bias, such that Llama-3-8B-Instruct and Llama-3.1-8B-Instruct were more

likely to select the first choice presented (p<.001), GPT-4o was also more likely to select the first choice presented albeit to a lesser degree (p=.004), and GPT-4 was actually more likely to select the last choice presented (p<.001). This is consistent with previous findings of order bias in LLMs[53,54]. The fact that LLMs, but not humans, display an order bias in this task raises the possibility that LLMs do not necessarily attain their high accuracy in a similar way to humans.

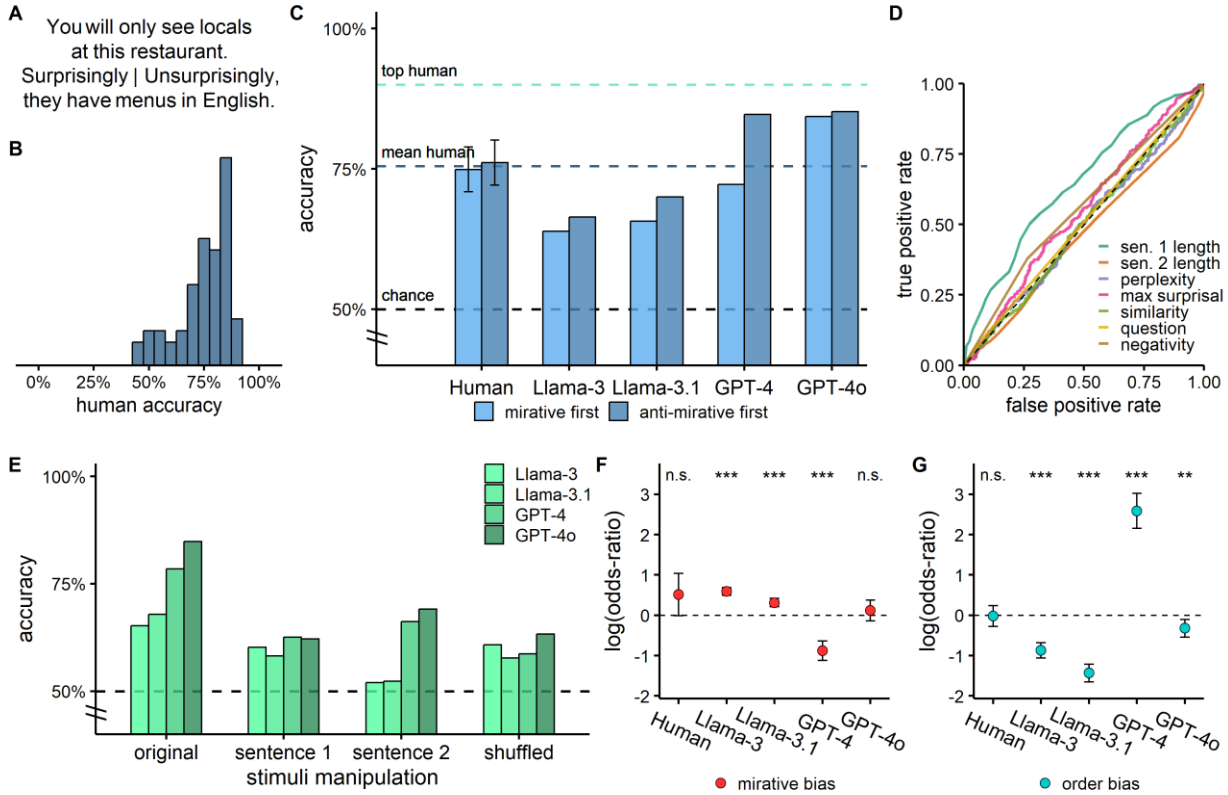

Figure 3. LLMS achieve near human performance on mirative polarity selection. *Mirative polarity selection is a novel task where participants and LLMs are presented with a sentence pair and asked to select whether it was connected with a mirative marker ("surprisingly") or an anti-mirative marker ("unsurprisingly"). We used 1000 sentence pairs (500 per marker) from the Discovery dataset (Sileo et al., 2019). Human participants were presented with 60 randomly selected stimuli (30 per marker).* ***A)*** *Example stimulus, presented in mirative first order. The correct choice is the mirative marker ("surprisingly, they have menus in English").* ***B)*** *Human accuracy distribution in the task.* ***C)*** *Accuracy on the task for human participants and several LLMs. Choice order with the mirative marker presented first is shown in light blue, and the reverse choice order with the anti-mirative marker presented first is shown in dark blue. Error bars show the 95% CI.* ***D)*** *AUC for several discrimination criteria are all close to chance level. Criteria include: length of first or second sentence in tokens, the perplexity and the max surprisal of the second sentence, the cosine similarity between the sentences, whether the first sentence is a question, and the presence of a negative marker in any of the sentences.* ***E)*** *LLM mean performance on several conditions of manipulated stimuli. Sentence 1: presented with the first sentence only. Sentence 2: presented with the second sentence only. Shuffled: the first and second sentences of different pairs were randomly shuffled within the same marker.* ***F-G)*** *Estimates for a mirative bias and a choice order bias, per model, obtained using logistic mixed-effects models.* ***F)*** *Mirative bias: positive values suggest higher probability of selecting the mirative marker over the anti-mirative marker, and negative values vice-versa. n.s. not significant. *** p<.001.* ***G)*** *Order bias: positive values suggest higher probability of selecting the second choice presented over the first, and negative values vice-versa. Error bars show the 95% CI. n.s. not significant. ** p<0.01. *** p<.001.*

General discussion

In this study, we assessed sensitivity to mirativity in both human participants and LLMs. We measured how the presence of a mirative marker ("surprisingly") affects subsequent expectations using a sentence-completion task, and whether humans and LLMs are able to detect expectation violations warranting the use of a mirative marker. Results show that both humans and LLMs use mirative markers as an indication for an upcoming expectation violation, and that both humans and LLMs display a similar level of sensitivity to mirativity, as measured by our tasks.

Within "predictive processing" theories[20,22], there is a clear advantage for giving a warning signal prior to an expectation violation, which allows a preemptive modification of expectations, thus reducing the would-be prediction error. Grice's cooperative principle of communication asserts that speakers aim to help their interlocutors process the conveyed message[55]. Along these lines, a speaker may use a mirative marker as part of the cooperative principle to help their interlocutor reduce their prediction error for an upcoming unexpected message. Thus, sensitivity to mirativity can provide an advantage for more efficient processing of information. Further studies can directly test this claim by measuring the effect of mirative markers on behavioral and neural correlates of prediction error.

As shown in part 1, human participants modified expectations upon encountering a mirative marker, as did LLMs. The expectation modification involved a reduction (but not an elimination) in the probability of the most-expected response, and an increase in entropy. The reduction in probability of the most-expected response may be considered a trivial result, as the literal meaning of mirative markers such as "surprisingly" is that the current message is not the most-expected one[30,28]. The increase in entropy can be interpreted as a general increase in the uncertainty as to the identity of the next upcoming word. This is because while mirative markers signal an upcoming expectation violation, they do not specify the content of the violation, leading the interlocutor to increase their expectations for many different upcoming words, all of which violate expectations. Additionally, mirative markers do not specify the exact location of the upcoming expectation violation (only that it will appear soon). During word-by-word prediction, this prevents the interlocutor from discounting the highly expected words, since the violation could appear later on. Instead, it leads to domain widening, where the set of plausible next words expands while preserving the most-expected words. Domain widening is congruent with the increase in entropy observed. Moreover, when comparing the top tokens of the LLM responses, overall token rankings remained stable but the probability decreased for the top 10-20 tokens and increased for

the rest of the tokens. This supports the notion that uncertainty about the location and identity of the expectation violation leads to expanded expectations when predicting the next word.

In a follow-up analysis, we used a large number of sentence fragments to investigate factors which influence the change in expectations in an LLM following a mirative marker. Using language models for measuring predictability and entropy of expectations is a standard method[56,45,43] and can be suggestive of the effects in human participants even without testing humans directly. Results show a "window of altered expectations" (in which mirative markers led to increased) to be approximately two sentences long or 5-40 words ahead. Notably, the stimuli used was not designed to contain expectation violation, and we theorize that in natural settings mirative markers alter expectation until encountering a violation, which likely will occur within two sentences. Entropy increase was consistent for expected content words and function words. For an illustrating example, for the sentence fragment "All that the brain has to work with are ___", the most-expected token was "the", which is a function word (a determiner). When preceded by the mirative marker "surprisingly", entropy nonetheless increased, although the word "the" is not related to the semantic content of the message. This result may be because less-expected content words remain possible in such positions (for example, "neurons"), or because mirative markers create a general uncertainty in expectations. Since our human experiments were designed to elicit nouns, we are not able to conclusively assess difference by word type and POS in human participants in this study. Furthermore, entropy increase was independent of the contextual constraint of the sentence fragments. The fact that even lower-constraining sentence fragments (wherein there isn't one clear expectation for the upcoming word) nonetheless see an increase in entropy suggests that mirative markers alter expectations at all levels, even weakly held ones. Additionally, this affirms that the increase in entropy is not due to regression to the mean (where extreme values of entropy would have become more moderate).

As shown in part 2, LLMs reached human performance level in selecting the mirative marker as the appropriate connector between a pair of sentences. Identifying if a sentence pair contains a violation of expectations is complex and requires several cognitive abilities: reading comprehension, detecting (often implicit) expectations by applying world knowledge and theory-of-mind in context, and recognizing mismatches between the expectations and the actual message. Thus, success on the task is far from trivial. Human performance varied considerably, ranging between chance level to 90% accuracy. This could possibly reflect individual differences in the ability to detect expectation violations. It could also reflect differences in the specific expectations people form due to different life experiences,

which would lead some to judge that a certain message contains a violation of expectations while others would disagree (but notice that the inter-subject percent agreement was around 68%, significantly above chance). It could also reflect the possibility that human participants differed on the level of attention and engagement with the task.

LLMs performed impressively at the task, reaching and exceeding average human level (although still below top human performers). A possible concern is that the stimuli used, taken from the internet, could have been in the training data for the LLMs we tested ("data contamination"), although we argue otherwise for several reasons: LLM performance is at human-average rather than ceiling level, accuracy dropped when tested on the first or second sentence only (which are sufficient by their own for retrieving a memorized sequence), and the order of the options presented systematically influenced LLM selection. An AUC analysis did not reveal any variable (e.g., sentence length) which could be used to discriminate the stimuli (see Fig. 3D), and performance dropped when sentence pairs were shuffled, ruling out some non-semantic property of the stimuli that the LLMs could have used to classify it. Additionally, a supplementary analysis revealed that the presence of a mirative marker affected LLMs' common-sense reasoning but not vocabulary testing (see Supplementary Materials). Taken together, this evidence suggests that LLMs' success on the task is likely due to an ability to identify expectation violations, which is a core part of their general sensitivity to mirativity.

The astounding breakthrough success of LLMs in recent years has raised questions about their ability to construct a world model[57,58] and a theory-of-mind[59,51,60]. A world model can be defined as an internal representation of the properties and causal dynamics of the physical world. Theory-of-mind can be defined as a model of the mental states of another agent, including their beliefs and expectations. Success in the mirative polarity selection task requires a basic level of both a world model and a theory-of-mind, because in order to identify what would constitute an expectation violation one must first have a good approximation of the expectation their interlocutor would form. There is ample evidence showing that humans possess an understanding of "folk physics", even at a young age[61–63]. Thus, a world model is helpful in informing about what their interlocutor would expect to happen, under normal circumstances. To take an example stimulus: "I saw the issue. Surprisingly/Unsurprisingly, it was easy to fix". To correctly select the mirative marker ("surprisingly"), one must i) have a world model wherein issues are usually difficult to fix, and ii) use their theory-of-mind to understand that their interlocutor would also expect the issue to be difficult to fix. The success of LLMs on the task suggests that LLMs may have some sort of a functioning theory-of-mind and informative world model (albeit not necessarily

similar in representation to humans), or at least that they display behaviors which would make it appear as though they have them. While this study did not aim to assess the extent, robustness, and human-likeness of the theory-of-mind and world models that LLMs may or may not possess, their performance in this study may provide some initial evidence for such capabilities, upon which future studies can be conducted.

As noted previously, LLMs displayed different biases than humans in the mirative polarity selection task. In terms of the tendency to select each marker, humans showed a non-significant mirative preference, meta-llama models showed a significant mirative preference, GPT-4 showed a significant anti-mirative preference, and GPT-4o showed no preference. Bayesian inference can explain the mirative bias: when the stimulus lacks sufficient information to determine its label, prior knowledge must be used instead, and the base frequency of "surprisingly" is substantially higher than "unsurprisingly" in natural language. LLMs were also influenced by the presentation order of choices, in line with previous research[53,54], while humans were not. Whether considering all participants or only the subset of participants who completed the task under both choice orders, no significant order bias was found. In contrast, the meta-llama models and GPT-4o displayed a significant preference towards the first choice presented, and GPT-4 displayed a significant preference towards the last choice presented. The combination of a last-choice bias and an anti-mirative bias renders GPT-4 as particularly un-human-like in this task.

Limitations

This study has several limitations. First, there are several known drawbacks of using online questionnaires administrated through the internet. Although participants were instructed to dedicate 20 minutes of their time and complete the tasks in an environment free from distractions, there is no way to verify this actually occurred. Nonetheless, participants' responses in the sentence-completions showed no indication of randomly typing words or misreading the sentence fragments, and participants' performance on the mirative polarity selection task was high. This suggest that, overall, participants were engaged with the tasks.

Another limitation is that, in the mirative polarity selection task, we assumed that each stimulus actually contains an expectation violation (or confirmation, for the anti-mirative label). This assumption is somewhat justified since the stimuli were naturally produced, but there is no way to independently verify this. Moreover, since the stimuli were taken from the internet, the identity of their authors (and relevant information such as whether they are fluent English speakers) is unknown, although we did

select stimuli which appeared well-formed and contained no clear misspellings. We take top human performance, at 90% accuracy, as a tentative approximation that 90% of the stimuli were discernable in nature and thus contained an expectation violation or confirmation.

Finally, in this study we treated the presence of a mirative marker as a sincere indicator of a violation of expectations. However, in natural conversation, sarcasm allows speakers to use markers for their opposite meaning[64]. While we believe this usage is rare, we cannot discount the possibility of human participants or LLMs treating the mirative marker (or the anti-mirative marker) as sarcastic, with the intention to indicate an opposite meaning.

Conclusions

In conclusion, this study researched the sensitivity of humans and LLMs to mirativity, the explicit marking of expectation violations. The two parts of this study can be viewed as investigating the two roles in discourse: the listener/reader who receives a message, and the speaker/writer who transmits it. Part 1, where we examined expectations following sentence fragments, is analogous to receiving and a message, since the listener/reader does not know what the upcoming words will be and generates expectations for them. Upon encountering a mirative marker, expectations are modified accordingly. Part 2, where we examined selecting the mirative or anti-mirative connector for sentence pairs, is analogous to producing and transmitting a message, since the speaker/writer knows the content of the message they would like to convey. If they recognize the message contains an expectation violation, they can use a mirative marker to indicate so. We conclude that both humans and LLMs use mirative markers as cues for calibrating their subsequent expectations during sentence processing, and both humans and LLMs accurately identify when mirative markers are appropriate, albeit with different biases. Together, this study highlights the effects of expectation management, and demonstrates how mirative markers serve as indicators when communicating and processing unexpected information.

Methods

Part 1: Completing sentence fragments with mirative markers

Participants

A total of 40 native English speakers with no diagnosed dyslexia or learning disabilities participated in this part of the study by completing an online questionnaire. Participants were recruited through Facebook posts and word of mouth. All participants completed high-school in an English-speaking country. All participants electronically signed an informed consent form and were compensated for their participation.

Stimuli

For our main analysis we created 30 novel sentence fragments. The sentence fragments were 4-10 words long, all contained a subject and verb, and all terminated where the object is expected to appear. The sentence fragments were constructed such that there was at least one appropriate object that can plausibly continue the sentence, although in many cases there was more than one plausible continuation. Each sentence fragment appeared in two conditions: the *neutral* condition where the sentence fragment began with a neutral marker ("yesterday"), and the *mirative* condition where the sentence fragment began with a mirative marker ("surprisingly").

Procedure

Human: Participants performed an online sentence-completion (cloze) task. They were instructed to type a plausible word that will continue each sentence fragment. Participants were presented with each sentence fragment once: 15 sentences in the neutral condition and 15 in the mirative condition, presented in a pseudo-random order (no more than 3 consecutive trials of the same condition). The assignment of sentence fragments to conditions was counterbalanced between participants. Due to an unfortunate set-up error, one sentence fragment was presented in the mirative condition only, and was excluded from analyses. Responses were recorded while correcting for any typos (any misspelling of, e.g., champagne: champane, shampane etc. was replaced with the correct spelling).

LLM: The following LLMs were included: Llama-3-8B/70B, Llama-3.1-8B/70B, and Llama-3.2-1B/3B (base versions)[65]. These LLMs were chosen because they are open source, allowing to calculate the probability of the top token and the overall entropy. The LLMs were accessed with permission through the *Hugging*

Face transformers library[66]. LLMs were presented with each sentence fragment twice, once per condition. For each sentence fragment, the full next token probability distribution was recorded.

Analysis

Human data: We calculated the most popular response under the neutral condition and its response probability under both conditions. We also calculated the entropy of the response distribution per sentence fragment, per condition. We then tested if the inclusion of a mirative marker modifies the probability of the top neutral response and the next word entropy using two-tailed paired t-tests. Probabilities were logit-transformed prior to testing[67].

LLM data: For each sentence fragment we calculated the next token entropy (calculated over the entire vocabulary) for the neutral and mirative conditions. We also recorded the top 10K tokens under the neutral condition and their probability in both the neutral and the mirative conditions. Similarly to humans, we then tested if the inclusion of a mirative marker modifies the probability of the top neutral response and the next token entropy using two-tailed paired t-tests. Probabilities were logit-transformed[67]. We also inspected the mean next token probability per marker, calculated across all sentence fragments, for each of the top 10K tokens in the neutral condition. Data points were smoothed using locally estimated scatterplot smoothing (LOESS) with span=10.

Follow up testing and analyses (LLM only):

We conducted a follow-up analysis to investigate the scope of the expectation-modification effect of mirative markers and the factors that modulate it. To this end, we used Llama-3.1-8B, the largest open source LLM we tested which has shown a significant increase in entropy comparable to human participants.

Stimuli: We selected 30 passages from the Provo corpus[49]. Passages were selected such that they contained a minimal number of punctuation marks and non-English characters, no connectors (such as "however", "for example") or other markers as the first word of the passage (which would have prevented us from adding a mirative marker in that position). We also made sure that the passage was not explicitly about expectations or surprises. Passages were 2-3 sentences long (39-62 words, mean sentence length 21.35 words). Passages were then converted into all possible sentence fragments by taking every subset of the passage from the third word onwards (e.g., "All that the", "All that the brain", "All that the brain has", "All that the brain has to", and so on…). Overall, there were 1,365 sentence fragments. Each sentence fragment appeared in two conditions: the neutral condition, where sentence

fragments began as they were found in the corpus, or the mirative condition, where sentence fragments began with a mirative marker ("surprisingly") that was added to the passage.

Procedure: procedure was identical to the main analysis. The LLM was presented with each sentence fragment twice, once per condition.

Analyses: As a dependent variable, we calculated for each sentence fragment the difference in the next token entropy between the mirative and neutral conditions (positive values indicate higher entropy in the mirative condition). To assess the scope of the mirative marker's effect on expectations, we used two separate methods. First, we fit a linear mixed-effects model to the differences in entropy, with a fixed effect of sentence number within the passage and random intercepts per passage. Second, we fit a LOESS regression to the difference in entropy with span=20 using the word number in passage. These methods allowed us to locate a "window of altered expectations", defined as the location and range of the increased entropy following a mirative marker. The size of the window could be measured in number of sentences or in number of words. The "window of altered expectations" was found to extend up to 2 sentences, ranging between 5 to 40 words from the mirative marker.

Following that, we further assessed two additional factors which may influence the increased entropy: the POS of the top predicted response (and whether it is a content or function word), and the level of contextual constraint per sentence fragment (i.e., to what extent does the sentence fragment limits the upcoming probable next tokens). Taking only the data within the "window of altered expectations", we then fit a linear mixed-effect model to the differences in entropy and tested for the significance of the fixed effects. The model included the predicted token's syntactic POS (obtained using an automatic POS tagger[68]), the entropy in the neutral condition (which is taken as a measure for the level of contextual constraint), a control variable of a cubic B-spline for the word number within the passage, and random intercepts per passage. For the effects of POS, a post-hoc test was performed, using estimated marginal means, to compare the content and function POS. All regressions were conducted using *lme4* package[69] in R[70].

Part 2: Identifying expectation violations

Participants

A total of 63 native English speakers with no diagnosed dyslexia or learning disability participated in this part of the study by responding to an online questionnaire. Participants were recruited through

Facebook posts and word of mouth. All participants completed high-school in an English-speaking country. Two different versions of the online questionnaire were presented, with a different order of the two presented choices. A subset of 22 participants completed both versions of the questionnaire. One participant was excluded from this study due to not completing the questionnaire. All participants electronically signed an informed consent form and were compensated for their participation.

Stimuli

For our main analysis we selected 1000 sentence pairs from the Discovery discourse marker dataset[50], 500 per label: for the *mirative* label, sentence pairs were connected with a mirative marker ("surprisingly"), while for the *anti-mirative* label, sentence pairs were connected with an anti-mirative marker ("unsurprisingly"). The sentences were originally taken from a corpus of natural text, and the mirative or anti-mirative connector was a part of the sentence pair in the original text. Thus, the connector which actually appeared in the original text constituted the correct label for that pair. A reason for using sentence pairs as the stimuli in this task is that pair structure lends itself to setting up an expectation in the first sentence, indicating a violation of that expectation with a mirative marker connector, and conveying the violation in the second sentence. Sentence pairs were selected such that they contained minimal punctuation marks or non-English characters, sentences appeared well-formed, there were no clear misspellings, and there were no sentences which clearly came from "non-communicative" texts such as movie scripts or website menus. When we selected the sentence pairs to be used as stimuli, the correct label (mirative or anti-mirative) was not known, in order to avoid a possible bias.

Procedure

Human: To estimate human level performance on this task, two lists of 30 randomly sampled sentence pairs (15 per label in each list) were used presented to human participants through an online questionnaire. Sentence pairs were presented in a 2-atlernative forced choice paradigm as follows: the first sentence in the pair was presented, and underneath it a choice was given between two possible choices, which were the second sentence in the pair either connected with a mirative or an anti-mirative marker (e.g., "You will only see locals at this restaurant. A) Surprisingly, they have menus in English. B) Unsurprisingly, the have menus in English.") Participants were instructed to select the most natural continuation of the first sentence out of the two choices. There were two possible versions of the questionnaire, one where the choice order presented was mirative marker first and another where the

choice order presented was anti-mirative marker first, for all stimuli in that version. The subset of participants who responded to both questionnaire versions were presented with different sentence pairs in each one, and did so with a break of at least a week between them.

LLM: The following LLMs were included: Llama-3-8B-Instruct, Llama-3.1-8B-Instruct, Llama-3.2-1B/3B-Instruct[65], GPT-3.5, GPT-4/4-0613[71], and GPT-4o/4o-mini[72] ("chat" versions). The meta-Llama series of LLMs were accessed with permission through the *Hugging Face transformers* library[66]. The chatGPT series of LLMs were accessed using the OpenAI API. LLMs were presented with the stimuli in a prompt and their text response was recorded. Each prompt began with the instructions: "Please select the most natural continuation of the text from the multiple-choice list. Respond with your choice only." Followed by the first sentence and two possible choices, which were the second sentence of the pair either connected with a mirative or anti-mirative marker, exactly like the presentation for the human participants. Responses were set to be deterministic and we considered the top token returned as the LLM's response. For the chatGPT series of LLMs, which are closed-source and cannot be made to respond deterministically, the text response did not always match the top token which was provided separately in the output. In those cases, we coded the LLM response as the top token provided, such that if it was the beginning of the mirative marker (*Sur/sur/ Sur/ sur*) the response was coded as mirative and if it was the beginning of the anti-mirative marker (*Un/un/ Un/ un*) the response was coded as anti-mirative, taking into account different capitalizations and possible inclusions of preceding spaces. If the response returned by the LLM did not begin with any of the markers, it was coded as an invalid response and excluded from later accuracy calculations. Each LLM was presented with all the sentence pairs twice, once where the choice order presented was mirative marker first and another where the choice order presented was anti-mirative marker first.

Analysis

Human data: Using the participants' responses, we calculated the accuracy and the response rate per label for each participant, and from that we calculated the mean ± SE of all participants. We also looked at the accuracy of the top performing participants as an additional benchmark to compare LLM performance against. Agreement between participants was calculated using Gwet's AC1 metric[73].

LLM data: Accuracy and response rate per label were calculated. An additional stricter measure of accuracy, which we called j*oint order accuracy*, was calculated by considering the LLM response as correct only if they selected the correct label for given sentence pair under both presentations with

different order of choices. We then compared LLM performance with the mean human performance and the top human performance.

Follow up testing and analyses (LLM only):

Data discriminability: To ensure that the high performance of the LLMs was derived from some ability to identify expectation violations and not by relying on other heuristics, we measured the discriminability of the data using several simple variables: the length of the first sentence or the second sentence (measured in tokens using the Llama-3 tokenizer), the perplexity and the max surprisal of the second sentence given the first sentence without any connecter (measured using Llama-3-8B base version), the cosine similarity between the first and second sentence (measured using OpenAI's embeddings model text-embedding-3-small), whether the first sentence was a question or not, and whether the first or second sentence contained any negativity markings (where the sentence pair includes any of the following words: *no/not/_n't/none/nothing/never/neither/cannot).* Discriminability was measured using the ROC and the Area Under the Curve (AUC) was calculated for each variable.

Manipulated stimuli: An additional test, using manipulated stimuli, was conducted on the best performing LLMs (Llama-3-8B-Instruct, Llama-3.1-8B-Instruct, chatGPT-4, chatGPT-4o). The manipulated stimuli included using only the first sentence of each pair, using only the second sentence of each pair, and using sentence pairs wherein the first and second sentences were shuffled randomly within the same label. Once again, each LLM was presented with all the sentence pairs twice, once where the choice order presented was mirative marker first and another where the choice order presented was anti-mirative marker first.

Biases: Beyond comparing human and LLM performance, we also compared their respective biases in the responses on the task: the mirative bias, which is the propensity to select the mirative marker, and the order bias, which is the propensity to select the first choice presented. We estimated the biases using a logistic mixed-effects regression using the mirative response rate as the dependent variable, an intercept and choice order as the independent variables, and a random intercept per stimulus. For human participants, we also included a random intercept per participant. The intercept and order coefficients extracted from the regression model were interpreted as the log odds-ratio to select the mirative marker over the anti-mirative marker and the log odds-ratio to select the second choice presented over the first choice presented, respectively. A more conservative estimate for the human

572 bias was calculated in the same manner but using only the 22 participants who completed both versions
573 of the questionnaire. All regressions were conducted using *lme4* package[69] in R[70].

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Competing interests

The authors declare no competing interests.

Data availability statement (mandatory)

The datasets generated and analyzed during the current study will be made available in an open-source public repository [LINK].