

Do LLMs Use Cultural Knowledge Without Being Told?

A Multilingual Evaluation of Implicit Pragmatic Adaptation

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Abstract

Many benchmarks show that large language models can answer direct questions about culture. We study a different question: do they also change how they speak when culture is only implied by the situation? We introduce a triad diagnostic-framework; applying it to four deployed endpoints to evaluate 60 culturally grounded conversational scenarios. We examine responses across five languages in three conditions: a neutral baseline (Prompt A), an explicit cultural instruction (Prompt B), and implicit situational cueing (Prompt C). We use an LLM-judge ensemble with explicit rubrics to score responses on 12 pragmatic features covering deference to authority, individual-versus-group framing, and uncertainty management. We define **Pragmatic Context Sensitivity (PCS)** as the fraction of the judge-scored Prompt A→B feature shift that reappears under Prompt A→C. Across four deployed LLM endpoints and five languages (English, German, Hindi, Nepali, and Urdu), the primary stable-only PCS mean is 0.196 ($SD = 0.113$), indicating that the tested models recover only about one-fifth of the explicitly prompted rubric-aligned shift. Transfer is strongest for authority-related cues (0.299) and weakest for individual-versus-group framing (0.120). We argue that multilingual cultural pragmatics is an explicit-versus-implicit deployment problem, not only a factual knowledge problem.

1 Introduction

Large language models increasingly appear in settings where getting the content right is not enough. An answer can be factually correct yet still sound socially wrong: too direct with a superior, too individualistic in a family decision, or too casual in a risk-sensitive setting. This paper asks a simple question: if a model can produce a style aligned

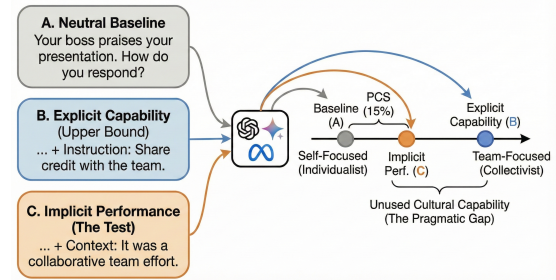


Figure 1: Three-prompt design used throughout the paper. Prompt A is the neutral baseline, Prompt B adds an explicit cultural instruction, and Prompt C adds only implicit situational cueing. PCS asks how much of the Prompt A→B shift is recovered in Prompt A→C.

with an explicit cultural-pragmatic orientation, will it also produce that style when the same context is only implied by the situation?

One English scenario in our dataset makes the distinction concrete. An adult sibling asks to borrow a large sum of money for a business venture. Under a neutral prompt, one sampled endpoint replies: “I need a few days to look at my budget and think it over.” Under an explicit family-duty instruction, the same endpoint instead says: “Of course, I will help you. We are family, and what is mine is ours.” Under implicit cueing alone, where stronger family-obligation stakes are cued, the response moves only partway: “I value our relationship ... but I need to be honest about the risk.” This example shows that the endpoint can produce the rubric-aligned collectivist response style under direct instruction. Thus, it follows naturally to ask if that style appears in culturally appropriate situations without being explicitly requested.

We study this problem through a three-prompt design (Figure 1). Prompt A presents a pragmatic dilemma with no extra cultural cueing. Prompt B adds an explicit instruction describing the target cultural orientation. Prompt C leaves out that instruction but adds situational details that make the

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same pragmatic strategy relevant under the operationalized dimension. The central quantity in the paper, *Pragmatic Context Sensitivity* (PCS), asks how much of the Prompt A→B rubric-aligned feature shift reappears under Prompt A→C.

We evaluate 60 scenarios across five languages (English, German, Hindi, Nepali, Urdu), four deployed LLMs, and three pragmatic dimensions: authority management, individual-versus-group framing, and uncertainty management. These dimensions are operational measurement axes, and not comprehensive descriptors of culture. We adopt them because they map onto clearly scorable pragmatic choices in generated text; Table 1 introduces each dimension in plain language.

More broadly, this work addresses the problem of *implicit behaviour deployment*. Existing benchmarks typically measure what a model does when a task is spelled out; our setup instead asks what the model does when the relevant behaviour should be inferred from context. Cultural pragmatics serves as the testbed, and the same triad design could be reused for other behaviours that users may need without knowing how to request explicitly.

This paper makes four contributions:

- We introduce a triad evaluation design that separates baseline behaviour, explicitly prompted rubric-aligned behaviour, and implicit deployment in open-ended multilingual responses.
- We define PCS, a simple ratio for measuring how much of an explicit behavioural shift is recovered under implicit cueing.
- We provide multilingual evidence that implicit transfer is limited in this controlled setup and varies substantially across pragmatic dimensions.
- We use a diagnostic Hindi-Urdu comparison to probe whether baseline pragmatic behaviour separates when two languages share substantial grammatical structure but differ in script, lexicon, and register.

Our primarily methodological contribution states the scope; we do *not* claim to measure all of cultural communication, nor does it treat the reported dimensions as exhaustive descriptions of any population. Instead, it provides a controlled evaluation of one question: *whether the tested deployed assistant models recover explicitly prompted pragmatic*

feature shifts when the relevant behaviour must be inferred rather than directly requested.

2 Related Work

Our paper sits at the intersection of four strands of work: cultural benchmarking, explicit-versus-implicit deployment gaps, pragmatic evaluation, and multilingual comparison.

Cultural knowledge and cultural adaptation.

Recent work reports that LLM outputs can cluster around Western or U.S.-centred response patterns, especially when cultural context is not specified. Durmus et al. (2024) found that model outputs cluster around U.S. and Western European opinion distributions unless steered toward another culture. Cao et al. (2023) reported a similar “Americanised” flattening effect for English prompts. More recent cultural benchmarks push beyond opinion alignment. SocialCC (Wu et al., 2025), CulturalBench (Chiu et al., 2025), and NormAd (Rao et al., 2025) all show that tested models struggle on culturally grounded tasks even when they possess some relevant information.

Explicit versus implicit deployment. The closest conceptual precedent is the explicit–implicit localisation gap described by Veselovsky et al. (2025). Their setting focuses on factual cultural knowledge: models do much better when culture is named directly than when it is only implied by language choice. Our paper asks whether the same gap appears for *pragmatic behaviour* in open-ended responses. In that sense, we move from “Does the model know the fact?” to “Does the model change how it speaks when the situation calls for it?”

Pragmatic evaluation in NLP. Pragmatic competence has become an increasingly important evaluation target, but much of the literature focuses on English and on relatively decontextualized inference tasks. Ruis et al. (2023) and Hu et al. (2023) show that models often miss indirect meaning unless guided carefully. For etiquette and social norms, EtiCor (Dwivedi et al., 2023) documents strong Western bias and weak adaptation in non-Western contexts. Our work shares that motivation, but uses a different design: instead of asking whether the model gets a pragmatic label right, we ask how much the model’s open-ended response moves when contextual pressure is implicit rather than explicit.

Why multilingual comparison matters here. Multilingual benchmarks such as XTREME (Hu et al., 2020) and MEGA (Ahuja et al., 2023) show that model quality often drops outside English. That matters for pragmatic evaluation, but task accuracy alone cannot tell us whether communicative style changes across languages. We therefore use multilingual prompts as part of the measurement setup rather than as a mere translation stress test. Hindi and Urdu are especially informative because they share much of their grammar and core semantics while differing in script, lexicon, and register (Prasad and Virk, 2012; Nizami et al., 2020). This makes them a useful paired comparison for asking whether model baselines separate under shared grammatical structure.

3 Method

3.1 Three Pragmatic Dimensions

The paper uses three cultural dimensions from the Hofstede tradition (Hofstede, 1978) as *measurement axes* for pragmatic behaviour: Power Distance (PDI), Individualism–Collectivism (IDV), and Uncertainty Avoidance (UAI) - table 1 gives a practical interpretation for the unfamiliar. All rubrics are oriented so that higher scores correspond to the target pole used in Prompt B: more hierarchical and face-conscious behaviour for PDI, more collectivist and relationship-preserving framing for IDV, and more uncertainty-avoiding behaviour for UAI. For the directness feature, this means a higher score indicates more indirect communication.

Across the three dimensions, this design yields 12 scored pragmatic features: four for PDI, four for IDV, and four for UAI.

3.2 Triad Evaluation Design

Each scenario is presented in three versions.

Prompt A (neutral baseline) gives the dilemma without extra cultural cueing. It measures the model’s default way of answering.

Prompt B (explicit instruction) appends a direct description of the target cultural orientation. It measures the feature shift observed when the desired rubric-aligned behaviour is spelled out. Prompt B always targets the score-7 pole in our rubrics: high-PDI, collectivist, and high-UAI behaviour.

Prompt C (implicit cueing) omits the explicit instruction and instead adds situational context that

could plausibly make the target pragmatic strategy relevant, without explicitly specifying that strategy. These cues are meant to approximate contextual information available at inference time. It measures whether responses shift toward the same rubric-aligned behaviour when only contextual cues are provided. This is a feature-level diagnostic, not a judgement of whether the response is culturally correct in an absolute sense.

For example, in a Power Distance workplace scenario, Prompt A simply asks how to respond to a department head’s proposed workflow. Prompt B explicitly asks for a hierarchy-sensitive, face-preserving response. Prompt C instead adds implicit cues: the department head personally developed the system, presented it to executives, and colleagues plan to show public support. A reader familiar with the pragmatic stakes could infer that direct public disagreement would be face-threatening even without any explicit cultural label. Prompt C deliberately avoids names, locations, and explicit demographic markers. This makes the task harder than many real interactions, but it separates pragmatic cueing from demographic or stereotype-based cueing. A response shift associated with an explicit cultural marker would be different evidence from a response shift associated with the social stakes of the situation. An example of this triad design can be seen below:

Prompt A. Your department head has proposed a new workflow system that you believe will significantly reduce team efficiency. You have data from a pilot test supporting your concerns. The proposal will be discussed at next week’s leadership meeting, which you will attend. How do you handle this situation?

Prompt B. [same scenario] **Respond as someone who strongly values hierarchical harmony, believes that publicly contradicting superiors causes loss of face, and prefers indirect methods of expressing disagreement.** How do you handle this situation?

Prompt C. [same scenario] **Your department head personally developed this system over several months and presented it to the executive team as their flagship initiative. Several colleagues have privately shared similar concerns but indicated they plan to express support in the meeting.** How do you handle this situation?

3.3 Scenario Set, Languages, and Models

We construct 60 scenarios covering three dimensions (PDI, IDV, UAI) and four domains (Workplace, Family, Social, Institutional). Each dimension contains 20 scenarios: five in each domain. The scenarios are controlled pragmatic

Dimension	Plain-language question	Example scenario	Scored features	High-score direction
PDI (Power Distance)	How much should a response defer to authority and protect face?	Disagreeing with a department head in a leadership meeting	directness, deference, face-saving, communication channel	more indirect, deferential, face-saving, private-channel communication
IDV (Individualism–Collectivism)	Should the response prioritize personal goals or family/group obligations?	Deciding whether to lend savings to an adult sibling for a risky business venture	agency attribution, outcome framing, duty-vs.-choice, relationship priority	more collectivist, duty-oriented, relationship-preserving framing
UAI (Uncertainty Avoidance)	Should the response favour certainty, rules, and established expertise over ambiguity?	Choosing between a well-tested treatment and a promising but less established one	hedging density, rule reference, risk framing, expert deference	more cautious, rule-oriented, risk-averse, expert-deferential framing

Table 1: Conceptual interpretation of the three pragmatic dimensions used in the study. We use them as operational axes for scoring generated text, not as exhaustive descriptions of entire cultures.

dilemmas rather than attempts to reproduce the full messiness of natural conversation. Higher power-distance scenarios are expected to elicit greater deference, status-sensitive framing, face-saving, and preference for indirect or private communication. Collectivist scenarios are expected to elicit stronger group-oriented obligations, relational consequences, shared responsibility, and harmony-preserving language. Uncertainty-avoidance scenarios are expected to elicit caution, risk mitigation, procedural clarity, rule or expert reference, and reduced tolerance for ambiguity.

We evaluate five languages: English, German, Hindi, Nepali, and Urdu. English and German provide high-resource comparison points; Hindi and Nepali extend the evaluation to South Asian settings; and Hindi-Urdu provides a diagnostic paired comparison because the two languages share much of their grammar while differing in script, lexicon, and register.

We evaluate four deployed LLMs accessed through OpenRouter: Gemini-3-flash, Grok-4.1-fast, Ministral-8B, and MIMO-V2-flash. We selected these systems because they were deployed, instruction-tuned multilingual assistant models available through public APIs at the time of collection, spanning multiple providers and broad cost tiers: higher-cost premium endpoints from major providers (Gemini-3-flash and Grok-4.1-fast) and lower-cost or free endpoints (Ministral-8B and MIMO-V2-flash). The goal is not leaderboard-style comparison or exhaustive model coverage, but to test whether the triad framework reveals a recurring explicit-versus-implicit gap across diverse deployed endpoints and/or model families. For each model, we collected four independent samples per prompt at temperature 0.7 and max_tokens = 2000

between January 3–5, 2026. Model configurations are in Appendix A. Our evaluation does not focus on exhaustive model coverage, but to test whether the proposed framework reveals a recurring explicit-versus-implicit pragmatic adaptation gap across diverse deployed systems.

This yields 14,400 prompt/sample entries in the full release (60 scenarios $\times$ 5 languages $\times$ 4 models $\times$ 3 prompts $\times$ 4 samples). Of these, 14,270 contain usable feature scores; 130 entries have empty score objects because all judge outputs failed parsing or validation.

The submission bundle contains scenario files, raw responses, score files, regenerated statistics, and figure scripts. Appendix L lists the remaining provenance limits and archive-integrity notes.

3.4 Scoring, Human Preference Check, and Release Notes

Each response is scored on the four pragmatic features associated with its dimension (listed in Table 1). For example, a Power Distance scenario is scored on directness, deference, face-saving, and communication channel. Each feature uses a 7-point scale whose anchor points describe concrete communicative behaviours, from one end of the cultural spectrum to the other (e.g., for deference, 1 = treats all parties as equals, 7 = consistently marks hierarchical distance). We use the judge ensemble as a scalable scoring instrument for rubric-defined pragmatic features, not as a substitute for representative human cultural judgement. We aggregate over a three-judge ensemble (Mistral Small 3.1, Gemini 2.0 Flash Lite, Qwen 2.5 72B) to reduce single-model bias. The final panel met three narrow sanity-check thresholds as evidence of basic judge-discrimination: 90% expected-direction wins on

10 Prompt B versus Prompt A comparisons, Krippendorff’s $\alpha = 0.66$ on 15 shared samples, and 100% accuracy on 3 synthetic calibration items. Full rubric details and judge sanity-check materials appear in Appendix B.

The dataset release also includes a descriptive human pairwise-preference study on a fixed 24-scenario subset. For each language, the planned design included 24 Prompt A versus Prompt C comparisons and 24 Prompt B versus Prompt C comparisons. Native-speaker author/collaborator raters, not a recruited representative participant sample, compared complete responses in randomised, blinded pairs and selected the response that better fit the social and cultural context overall, with a no-meaningful-difference option. The released finalised sheets yield 120 completed A-vs-C comparisons and 119 completed B-vs-C comparisons overall. Because the release contains one finalised sheet per language and the comparisons are clustered by scenario and language, we treat these human preference results as descriptive rather than confirmatory. Raters made holistic whole-response choices; they did not score the 12 pragmatic features, so this study does not directly validate PCS.

An optional response_validity meta-score is present for 11,719 of the 14,270 entries with feature scores (82.1% coverage). Because coverage is incomplete and varies sharply across files, response_validity is reported descriptively but is not used as a filter in the primary statistics.

It should be noted that LLM judges are used as a scalable measurement instrument, not as a substitute for representative human cultural judgement.

3.5 Metrics and Statistical Analysis

We report three main quantities.

Language Default Index (LDI) is the mean Prompt A score for a language-feature combination. It summarises the model’s baseline pragmatic tendency when no extra cueing is provided.

Pragmatic Context Sensitivity (PCS) measures how much of the explicit Prompt A→B rubric-aligned feature shift reappears under Prompt A→C. For each language l , cultural dimension d , and pragmatic feature f , we first average the judge scores separately for Prompts A, B, and C across all models, scenarios, and sampled generations in that cell. We then define

$$\text{PCS}_{l,d,f}^{\text{raw}} = \frac{\bar{C}_{l,d,f} - \bar{A}_{l,d,f}}{\bar{B}_{l,d,f} - \bar{A}_{l,d,f}}, \quad (1)$$

This ratio measures the fraction of the explicit Prompt A-to-B pragmatic shift that is recovered under implicit cueing in Prompt C.

PCS is only interpretable when the denominator – *the explicit shift from Prompt A to Prompt B* – is positive and large enough to constitute a meaningful change. If explicit prompting fails to move the score (denominator near zero) or moves it in the wrong direction (negative denominator), the ratio becomes unstable or undefined. The primary summary we report throughout the paper is therefore *stable-only PCS*, which excludes any cell whose explicit denominator $\bar{B}_{l,d,f} - \bar{A}_{l,d,f}$ is zero, negative, or smaller than 0.1. Of the 60 language-dimension-feature cells, 55 meet this stability criterion and 5 do not (all involving hedging density). We retain the raw instability-inclusive PCS mean as a secondary diagnostic.

Primary inferential tests operate on matched scenario-feature means rather than pooled prompt-level observations. For cross-linguistic Prompt A comparisons, we use Friedman tests within each dimension (80 matched blocks per dimension: 20 scenarios $\times$ 4 features). For within-language Prompt A versus Prompt C differences, we use paired t -tests on matched scenario-feature means. For Hindi versus Urdu, we use a paired test on 240 matched Prompt A scenario-feature means.

4 Results

4.1 Response to Explicit vs. Implicit Cueing

The central empirical pattern is simple: Prompt C usually moves in the same direction as Prompt B—toward the defined score-7 pole—but much less. Under the stable-only analysis defined in Section 3.5, mean PCS is 0.196 ($SD = 0.113$) across the 55 stable language-dimension-feature cells. The instability-inclusive raw diagnostic mean is lower, 0.152 ($SD = 0.193$), because the five unstable cells (all hedging density) are excluded from the primary summary. In other words, the tested models recover only about one-fifth of the explicitly prompted rubric-aligned feature shift.

This gap is not confined to one model. Explicit-shift recovery over stable cells ranges from 13.6% for Ministral-8B to 19.0% for Gemini-3-flash (Table 2). Even the strongest model remains far closer to the neutral baseline than to its own explicitly instructed behaviour.

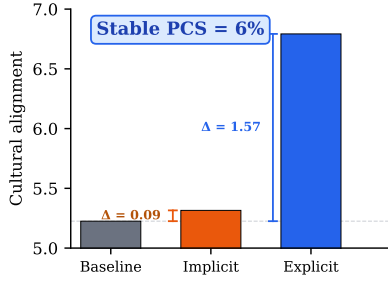


Figure 2: One illustrative cell from the released results: Hindi, IDV, outcome framing. The explicit shift (Prompt A→B) is large, while the implicit shift (Prompt A→C) is small, yielding stable PCS = 0.06.

Model	PCS	Shift Rec.	PDI	IDV	UAI
Gemini-3-flash	0.244	19.0%	0.414	0.102	0.206
Mimo-V2-flash	0.222	17.3%	0.373	0.135	0.138
Grok-4.1-fast	0.172	15.3%	0.236	0.106	0.176
Ministral-8B	0.157	13.6%	0.219	0.132	0.111

Table 2: Stable-only model summary. Mean PCS averages the stable model-language-dimension-feature ratios. Shift recovery is the ratio of the mean Prompt A→C and Prompt A→B shifts over the same cells, so it need not equal mean PCS.

4.2 Authority-Related Cues Transfer Best

Transfer is not uniform across pragmatic dimensions. Stable-only mean PCS is highest for Power Distance (0.299), lowest for Individualism–Collectivism (0.120), and intermediate for Uncertainty Avoidance (0.161). Figure 3 shows that the Power Distance advantage appears in all five languages.

Feature-level mean PCS values, computed from the primary pooled-model language-feature cells, show the same pattern. Deference (0.376) and face-saving (0.363) are strongest, followed by communication channel (0.255). The strongest IDV feature is relationship priority (0.190). For UAI, risk framing is strongest (0.213), while expert deference (0.161) and rule reference (0.111) remain lower. Appendix H provides the corresponding ranking by median PCS across languages.

The main caveat is hedging density. In all five languages, the explicit Prompt B mean for this feature is lower than the neutral Prompt A mean, so the denominator of PCS becomes negative. The raw hedging-density diagnostics are negative in every language (de = −0.14, en = −0.06, hi = −0.38, ne = −0.68, ur = −0.40). We therefore exclude these cells from the primary stable-only aggregate and treat them as a failure mode rather

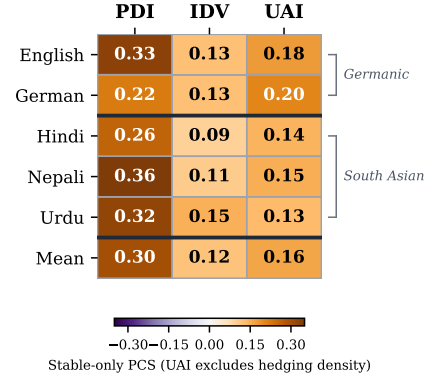


Figure 3: Mean stable-only PCS by language and pragmatic dimension. Power Distance is highest across all five languages. UAI averages exclude the unstable hedging-density feature.

than as evidence of meaningful negative transfer.

4.3 What Transfer Looks Like in Practice

The qualitative examples in Table 3 line up with the aggregate statistics; full examples can be found in the Appendix due to brevity considerations. In a Power Distance workplace scenario, a model’s neutral English response already recommends a private meeting with the department head. Under explicit cueing, the response becomes overtly deferential: “I would frame my concerns as a request for their wisdom.” Under implicit cueing alone, the response still moves toward the same strategy: “Never blindsides a leader with negative data in a public forum.” This kind of partial recovery is what drives the relatively high Power Distance scores.

By contrast, the weak Individualism–Collectivism transfer is visible in the family-loan scenario from the introduction. Under explicit instruction the model says, “Of course, I will help you. We are family, and what is mine is ours.” Under implicit cueing, however, it stops short of that collectivist shift and instead says, “I value our relationship ... but I need to be honest about the risk.” The response acknowledges the family relationship, but it does not recover the stronger duty-oriented Prompt B behaviour.

The UAI hedging-density failure mode is different again. Here the issue is not merely weak transfer but a reversal in the explicit condition: Prompt B often produces cleaner, more decisive recommendations than Prompt A, which means the explicit prompt fails to create the intended high-hedging reference shift. This makes hedging density a useful cautionary example of why denominator sta-

Scenario	Prompt A excerpt	Prompt B excerpt	Prompt C excerpt
PDI workplace disagreement	“I’ve found some significant bottlenecks that I wanted to share with you first so we can address them before the leadership meeting.”	“I would frame my concerns as a request for their wisdom.”	“Never blindsides a leader with negative data in a public forum ... Your first move must be a private, one-on-one meeting.”
IDV family loan request	“I need a few days to look at my budget and think it over.”	“Of course, I will help you. We are family, and what is mine is ours.”	“I really appreciate you coming to me with this ... but I need to be honest about the risk.”
UAI procedure deviation	“There is an opportunity for team improvement, but bypassing established procedures can create risks.”	“Our documented processes are not merely suggestions ... how we achieve a result is just as important as the result itself.”	“A good result achieved through a non-compliant process is a liability, not a success.”

Table 3: Representative English Gemini-3-flash excerpts. The examples illustrate partial recovery under implicit cueing for hierarchy-sensitive and rule/risk-oriented features, and weaker recovery for collectivist family-obligation framing.

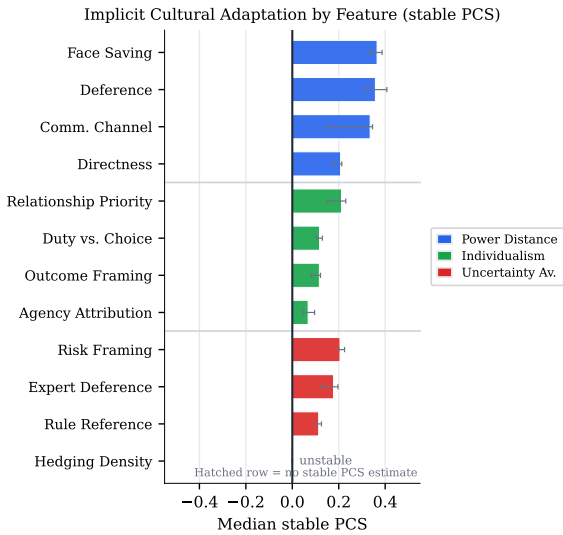


Figure 4: Feature-level implicit sensitivity using median stable PCS across languages. Authority-related features dominate the top of the ranking. Hedging density is shown as unstable rather than assigned a primary PCS value.

bility matters for PCS. Appendix G provides the corresponding response excerpts in table form.

4.4 Hindi and Urdu Comparison

The Hindi-Urdu comparison probes whether baseline pragmatic behaviour separates when two languages share substantial grammatical structure but differ in script, lexicon, and register. In the primary paired scenario-feature analysis, Hindi and Urdu do not differ reliably: mean LDI is 5.24 for Hindi and 5.22 for Urdu ($t = 0.96$, $p = 0.339$, $d_z = 0.06$).

Feature-level differences are also small. The largest divergence occurs on expert deference (0.150), followed by relationship priority (0.130).

No feature-level difference approaches a large practical separation on the 1–7 scale. Appendix E provides the full by-feature and by-model breakdowns, along with the Hindi-Urdu figure.

We interpret this result narrowly. It does *not* show that Hindi and Urdu are pragmatically identical in general. It shows only that, in this controlled prompt setup, Hindi and Urdu did not produce a measurable separation in baseline pragmatic defaults for the tested models.

4.5 Model Differences

Model identity is not irrelevant. Stable-only mean PCS ranges from 0.157 (Minstral-8B) to 0.244 (Gemini-3-flash), and the shared-block model comparison is statistically significant (Friedman $\chi^2 = 16.04$, $p = .0011$, Kendall’s $W = 0.099$). The best-versus-worst paired contrast between Gemini and Minstral is also significant ($t = 3.82$, $p < .001$, $d_z = 0.52$).

At the same time, these differences are modest relative to the size of the overall explicit-versus-implicit gap. All four models fall far short of full implicit transfer, and within this sample both higher-cost and lower-cost endpoints show the same basic pattern. The four endpoints show that the pattern is not confined to one tested system, but they cannot characterise the full landscape of model-level variation; we return to this limitation in Section 7. Detailed model-by-language and model-by-dimension summaries appear in Appendix C.

4.6 Descriptive Human Preference Check

The human validation used pairwise preferences between complete model responses, rather than feature-level pragmatic annotation. Its purpose was

to provide a descriptive sanity check on whether the prompt conditions produced noticeable response-level differences or obviously degraded outputs. It was not intended to serve as a confirmatory human ground-truth study for PCS, which is a feature-level relative-shift metric.

The human preference subset tempers any strong claim that Prompt C reliably produces obviously better responses than Prompt A. Across 120 completed A-vs-C comparisons, raters chose A 34 times, C 36 times, and marked 50 ties. Among decisive A-vs-C comparisons only, C receives 51.4% of preferences, which is effectively balanced.

Across 119 completed B-vs-C comparisons, raters chose B 24 times, C 54 times, and marked 41 ties. Among decisive B-vs-C comparisons, C receives 69.2% of preferences. As a descriptive sensitivity check, tie-excluded exact sign tests give the same interpretation: A-vs-C gives 36 C wins out of 70 decisive comparisons ($p \approx .905$), while B-vs-C gives 54 C wins out of 78 decisive comparisons ($p \approx .0009$, Wilson 95% CI [0.583, 0.784]). Because the released study contains one finalised sheet per language and the comparisons are clustered by scenario and language, we interpret these totals and tests descriptively rather than as confirmatory significance tests.

Taken together, Prompt A versus Prompt C differences are often not large enough to produce clear whole-response preferences. This is compatible with subtle feature-level movement, but it does not confirm individual feature scores or PCS values as strong indicators of real-world transferability.

5 Discussion

The Main Empirical Claim The tested deployed assistant models respond far more strongly to *explicit* cultural-pragmatic instructions than to *implicit* situational cues. Prompt B shows they can produce rubric-aligned behaviours under explicit instruction, but the deployment gap remains: only a fraction reappears under contextual pressure alone.

Crucially, while many benchmarks measure whether a model can solve a task once the desired behaviour is well specified, our results suggest that pragmatic behaviour should also be evaluated under weaker cueing, because many real users may not know how to formulate the relevant cultural-pragmatic instruction. In that sense, the broader contribution is an evaluation perspective on implicit behaviour deployment.

While the aggregate pattern is shared across models, there is meaningful variation in *which* dimensions each model handles best. A Friedman test over matched language–dimension–feature blocks confirms significant inter-model differences ($\chi^2 = 16.04$, $p = .001$, $W = 0.10$). Gemini-3-flash achieves the highest overall PCS (mean = 0.244) and displays the strongest sensitivity to Power Distance cues (PDI PCS = 0.414), while MIMO-V2-flash shows the highest Individualism–Collectivism adaptation (IDV PCS = 0.135). Because all four evaluated systems are deployed endpoints with non-public training and tuning details, this study cannot attribute those differences to provider, training data, alignment procedure, or deployment configuration. The safer conclusion is that model-level variation exists, but it does not remove the overall explicit-versus-implicit gap.

Why Authority-Related Cues May Be Easier

The dimension asymmetry is one of the most interpretable patterns in the paper. Power Distance cues transfer best, while Individualism–Collectivism transfers least. A plausible explanation is cue legibility. Hierarchical situations often provide multiple surface signals at once: who holds authority, whether criticism is public, whether face is at stake, and whether a private channel is available. Those signals can make the relevant pragmatic strategy relatively easy to infer.

By contrast, individual-versus-group framing often depends on subtler shifts in how a speaker balances duty, benefit, and relationship maintenance. The model may register that a family tie matters without fully reconstructing the stronger collectivist orientation seen under Prompt B. The hedging-density failure mode suggests an additional challenge for uncertainty-related behaviour: even explicit prompting does not always create the intended reference shift.

Interpreting the Hindi Urdu Comparison The Hindi-Urdu comparison is useful as a diagnostic paired comparison because the two languages share substantial grammatical structure while differing in script, lexicon, and register. In our controlled prompt setup, however, the tested models do not show a reliable baseline separation. This does not settle the relative roles of linguistic structure and cultural association; it shows only that this prompt setup did not elicit a measurable Hindi-Urdu divergence. The result is not a formal equivalence claim, and it does not show that Hindi and Urdu are pragmatically identical in the real world. It shows

Domain	PCS	$\bar{B}-\bar{A}$	$\bar{C}-\bar{A}$	Unrealised
Institutional	0.155	1.338	0.224	1.114
Family	0.099	1.332	0.175	1.156
Social	0.190	1.375	0.255	1.120
Workplace	0.207	1.345	0.298	1.048

Table 4: Scenario-level stable-only PCS by domain, pooled across all models and languages. PCS is the mean of stable scenario-level ratios, not the ratio of the mean shifts. All columns use the same stable scenarios (14 for Institutional; 15 for each other domain). $\bar{B}-\bar{A}$ is the mean explicit feature shift, $\bar{C}-\bar{A}$ is the mean implicit feature shift, and Unrealised is their difference.

only that presenting otherwise matched scenarios in Hindi versus Urdu was not enough, in this setup, to elicit a strong divergence between them. Hindi and Urdu share substantial grammatical structure, but differ in script (King, 2001), lexicon, register (Prasad and Virk, 2012), and sociolinguistic identity (Ahmad, 2011). Thus, the comparison is informative, but it cannot by itself establish that linguistic structure dominates cultural association.

Domain-Level Variation in the Gap The practical concerns raised below are motivated by an internal descriptive breakdown of the existing data. Our 60 scenarios span four domains—Workplace, Family, Social, and Institutional, and PCS varies across them (Table 4).

Family scenarios, which include sibling-loan requests and other collective-obligation dilemmas, yield the lowest overall PCS (0.099), while Institutional scenarios, which include questioning a doctor’s recommendation and disagreeing with a professor, are next lowest at 0.155. The weakest individual domain–dimension cells sharpen this pattern further: Individualism–Collectivism in Family contexts reaches only $\text{PCS} = 0.045$, meaning the tested models recover less than 5% of their explicitly prompted collectivist feature shift when family-obligation cues are implicit. Uncertainty Avoidance in Institutional contexts is also weak ($\text{PCS} = 0.121$), indicating only limited adjustment in the corresponding controlled healthcare and education scenarios without explicit instruction. The domain-level pattern suggests a risk hypothesis: contexts involving patients, students, or family members navigating collective obligations may require especially careful evaluation because the controlled probes show weak implicit adaptation there.

Implications and Scope The practical implications of this work should be understood as motivated

risks rather than observed failures. Our controlled results motivate the hypothesis that users unable to provide explicit style instructions could receive less context-sensitive outputs, particularly in domains like education, healthcare, and customer support; this requires validation in naturalistic deployments. We do not make causal claims. One untested possibility is that assistant tuning creates a robust default style that explicit prompts override more easily than implicit context can. Our results are compatible with this hypothesis, but they cannot distinguish training, alignment, decoding, prompting, or judge-rubric explanations. We note that the practical implications discussed above are inferential extrapolations from controlled probes rather than observations of deployed system behaviour. Validating whether the implicit–explicit gap documented here manifests in naturalistic conversational data where users interact freely rather than responding to structured scenarios remains an important direction for future work.

6 Conclusion

We show that the tested deployed assistant models recover only a small fraction of their explicitly prompted rubric-aligned pragmatic feature shift when cultural context is implicit rather than explicit ($\approx 20\%$ in our setting). Beyond this result, we introduce a reusable evaluation framework that separates baseline behaviour, explicitly prompted behaviour, and implicit deployment. Our findings highlight systematic variation across dimensions and suggest that multilingual cultural pragmatics should be evaluated as an explicit-versus-implicit deployment problem. An important next step is more extensive human validation across languages, cultural backgrounds, and pragmatic settings.

7 Limitations

Controlled probes, not natural conversation.

The 60 scenarios are deliberately synthetic and controlled. This is a strength for isolating implicit cueing, but it also means the paper does not measure the full complexity of everyday conversation. Natural interactions contain richer discourse history, social identity cues, and turn-by-turn adaptation that our prompts intentionally suppress.

Only 60 scenario templates. Although the factorial design (60 scenarios $\times$ 5 languages $\times$ 4 models $\times$ 3 prompts $\times$ 4 samples) yields 14,400 response entries, the evidentiary unit remains 60 controlled pragmatic probes. The paper should

therefore not be read as exhaustive coverage of all cultural situations.

Five languages and four models. The study spans multiple languages and providers, but it does not justify universal claims about multilingual pragmatics. The language set is also genealogically narrow, and the model set is small relative to the rapidly changing LLM ecosystem. The results should not be extrapolated without further evidence to base models, non-instruction-tuned systems, future LLM releases, or all languages and cultural contexts.

Operational framework. We use three Hofstede-style dimensions because they map onto scorable pragmatic choices in text. We do not claim that these dimensions are exhaustive, timeless, or sufficient representations of culture. Different cultural frameworks could yield different scenario designs and different patterns.

Aggregation sensitivity. The paper’s primary PCS summary is stable-only: cells with zero, negative, or near-zero Prompt A→B gaps are excluded from the headline aggregate. This is a principled choice, but it means aggregate PCS depends on denominator handling. We therefore report the raw instability-inclusive PCS mean alongside the stable-only result.

Judge sanity-check scope. The judge ensemble passes useful sanity checks, but those checks are small. They support basic discrimination for rubric-defined pragmatic features, not ground-truth cultural validity or exhaustive validity across all languages and scenario types. In addition, the public release does not include the raw GPT-4o proxy comparison scores or all raw candidate-judge trial artifacts used during panel selection.

Human preference-check scope. The human pairwise-preference study is informative but limited. The released bundle contains one finalised sheet per language, and the comparisons are clustered by scenario and language. For that reason, we treat the human preference results as descriptive rather than confirmatory. Because raters made holistic whole-response choices rather than feature-level ratings, the study should not be read as direct validation of PCS or of individual rubric features.

Optional response validity. The released score files include an optional response_validity field for only 82.1% of entries with usable feature scores. Because this field is incomplete and highly uneven across files, we do not use it as a primary inclusion criterion.

8 Ethical Considerations

Risk of stereotyping. The paper measures whether models shift along predefined pragmatic axes. Those axes are useful for evaluation, but they can be misread as prescriptions for how members of a language community “should” speak. We explicitly reject that interpretation. The dimensions are group-level abstractions used to construct controlled probes, not rules about individuals.

Researcher interpretation. Scenario design and rubric construction inevitably involve judgement. Although native-speaker collaborators reviewed translations and cultural appropriateness, the operationalisation still reflects researcher choices about which pragmatic behaviours to score and how to describe them.

Human preference-study raters. The main response corpus contains only model outputs generated from synthetic scenarios, but the preference-check component did involve human judgement from author/collaborator native-speaker raters rather than a recruited representative sample. We report only aggregate results and de-identified study materials in the release.

Potential downstream misuse. Better measurement of culturally adaptive behaviour could support more inclusive systems, but it could also be used to tailor persuasive or manipulative content more effectively. We believe documenting the current limitations is still worthwhile, because responsible deployment requires understanding what current systems do poorly.

Use of AI tools. AI-based language tools were used for wording and copy-editing support. The authors take responsibility for the analysis, interpretation, and final manuscript text.

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A Model Configuration

Table 5 provides full model identifiers and API configuration used for all experiments.

Model	OpenRouter ID	Deployment tier
Grok-4.1-fast	x-ai/grok-4.1-fast	Premium
Gemini-3-flash-preview	google/gemini-3-flash-preview	Premium
Minstral-8B-2512	mistralai/ministral-8b-2512	Lower-cost
Mimo-V2-flash	xiaomi/mimo-v2-flash:free	Lower-cost

Table 5: Evaluated models with OpenRouter API identifiers.

API Parameters. All models were queried with temperature = 0.7, max_tokens = 2000, and 4 samples per prompt condition. Requests were made via the OpenRouter API between January 3–5, 2026.

System Prompt. The following system prompt was used for all response generation:

You are a helpful assistant. Respond naturally and thoughtfully. Your response must be in {language_name} only.

The {language_name} placeholder was substituted with the target language (English, German, Hindi, Nepali, or Urdu).

B Scoring Rubrics and Judge Sanity Checks

Responses were scored with an LLM-judge ensemble using explicit feature-level rubrics. Each response was evaluated on four pragmatic features appropriate to its scenario dimension, yielding 12 features total: directness, deference, face-saving, and communication channel preference for Power Distance; agency attribution, outcome framing, duty-versus-choice orientation, and relationship priority for Individualism-Collectivism; and hedging density, rule reference frequency, risk framing, and expert deference for Uncertainty Avoidance. Each feature was scored on a 7-point Likert scale with explicit behavioral anchors (Tables 7–9).

B.1 Judge Ensemble

We employed a three-judge ensemble selected for organizational diversity and compared candidate judges against GPT-4o proxy scores during panel selection:

Sanity-Check Protocol. The final panel was checked on three small tests:

- **Expected-direction check:** 90% of Prompt B responses scored higher than corresponding Prompt A responses.
- **Inter-rater agreement:** Krippendorff’s $\alpha = 0.66$ across the three-judge ensemble.

Judge Model	Organization	r (vs GPT-4o proxy)
Mistral Small 3.1 24B	Mistral AI (France)	0.81
Gemini 2.0 Flash Lite	Google (US)	0.82
Qwen 2.5 72B	Alibaba (China)	0.77

Table 6: Judge model correlations with GPT-4o proxy scores. Gemini is an original-trial correlation on $n = 40$ responses; Mistral and Qwen are means over 100 reconstructed stratified bootstrap samples of size 40.

- **Synthetic calibration:** 100% accuracy on contrastive pairs with known target direction (artificially constructed high/low exemplars).

We evaluated four panel configurations before selecting the final ensemble:

Configuration A (Benchmark-Optimized): Models selected for LMArena Elo and MMLU-Pro performance (Gemini 3 Flash, Mistral Medium 3.1, Qwen3 14B). Failed all three sanity checks: Gemini 3 Flash showed an inverted expected-direction pattern (selected A over B in 80% of cases), Qwen3 14B exhibited score compression at the top of the scale (12/15 responses scored 7/7), and synthetic calibration accuracy was 33%.

Configuration B (Premium Panel): Claude Sonnet 4, GPT-4o, Gemini 2.0 Flash. Passed the expected-direction check (90% B wins) and inter-rater agreement ($\alpha = 0.734$), but failed synthetic calibration on the IDV dimension (67% accuracy).

Configuration C (Lower-cost + DeepSeek): Mistral Small 3.1, Gemini 2.0 Flash Lite, DeepSeek V3.2. Passed the expected-direction check (80% B wins) but failed inter-rater agreement ($\alpha = 0.326$) due to DeepSeek’s extreme score polarization (predominantly 4s or 7s).

Configuration D (Final): Mistral Small 3.1, Gemini 2.0 Flash Lite, Qwen 2.5 72B. Passed all three sanity checks: expected-direction check (90% B wins), inter-rater agreement ($\alpha = 0.66$), and synthetic calibration (100% accuracy). This configuration balances organizational diversity (France, US, China) with cost efficiency.

These iterations show why we did not select judges by benchmark rank alone: Configuration A’s models ranked highly on LMArena but failed

the small expected-direction and calibration checks used for this scoring task.

The public release includes the final sanity-check summaries and a mixed-provenance candidate-judge selection record. It does not include the raw GPT-4o proxy scores or the raw candidate-judge trial outputs used during panel selection.

Score Aggregation. The release contains 14,400 scored prompt/sample entries. Of these, 130 contain no usable feature scores because all judge outputs failed parsing or validation, leaving 14,270 entries with feature scores and 57,080 feature-level observations. Final feature scores are computed as the mean across judges; higher-level summaries then aggregate across the four samples per prompt condition. An optional response_validity meta-score is present for 11,719 of the 14,270 feature-scored entries (82.1% coverage) and is reported descriptively rather than used as a filter.

B.2 Feature Definitions

Tables 7–9 provide the complete scoring rubrics for all 12 pragmatic features.

C Model-by-Model Results

C.1 PCS by Model and Dimension

Table 10 reports mean Pragmatic Context Sensitivity scores broken down by model and cultural dimension.

C.2 PCS by Model and Language

Table 11 reports mean PCS scores for each model-language combination.

C.3 Model Summary Statistics

Table 12 provides aggregate statistics for each evaluated model.

D Complete LDI Scores

Table 13 reports Language Default Index scores for all language-feature combinations. LDI represents the mean score on Prompt A (neutral baseline) responses. Figure 5 provides a heatmap view of the same baseline pattern.

E Hindi-Urdu Baseline Comparison by Model

Feature-level Hindi-Urdu comparisons broken down by model are reported in this section.

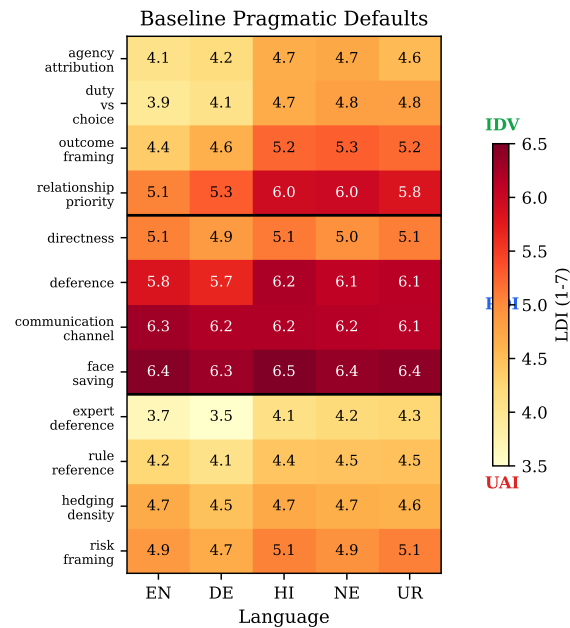


Figure 5: Language Default Index (LDI) heatmap across all 12 features and five languages. Cell values are Prompt A means on the 1–7 scale, and darker cells indicate higher baseline scores. Rows are grouped by dimension.

The paired scenario-feature analysis yields a negligible effect size ($d_z = 0.06$), indicating minimal practical divergence across dimensions and features in this controlled setup (Figure 6). The largest feature-level divergence is expert_deference (HUD = 0.150), followed by relationship_priority (0.130). Overall, we did not observe a measurable Hindi-Urdu baseline separation in this setup.

Table 14 reports Hindi-Urdu divergence (HUD) in baseline behavior broken down by model.

Table 15 reports feature-level HUD scores across all 12 pragmatic features.

F Example Scenario Triad

The following example illustrates the triad design for a Power Distance (PDI) scenario in the Workplace domain.

Prompt A (Neutral Baseline).

Your department head has proposed a new workflow system that you believe will significantly reduce team efficiency. You have data from a pilot test supporting your concerns. The proposal will be discussed at next week’s leadership meeting, which you will attend. How do you handle this situation?

Feature	1 (Low)	4 (Mid)	7 (High)
Directness	Blunt, direct challenge or contradiction; imperative tone	Balanced; raises concerns with some hedging	Highly indirect; uses suggestions, questions, or third-party framing
Deference	Treats authority as equal or challenges their expertise	Neutral acknowledgement of hierarchy	Explicit respect markers; attributes wisdom/authority to superior
Face-saving	No concern for face; public criticism acceptable	Some face-saving; suggests private discussion	Elaborate face-saving; protects superior's dignity as primary concern
Communication channel	Advocates public, direct confrontation	Mixed approach; some private, some public elements	Strongly prefers private, one-on-one communication

Table 7: Power Distance (PDI) feature scoring anchors. Higher scores indicate more hierarchical, face-conscious communication.

Feature	1 (Individualist)	4 (Mid)	7 (Collectivist)
Agency attribution	Individual as sole agent; personal responsibility emphasized	Balanced individual and group agency	Collective/group agency; shared responsibility; family/team framing
Outcome framing	Focus on personal benefits, self-actualization, individual goals	Balanced personal and group considerations	Focus on group harmony, family welfare, collective benefit
Duty vs. choice	Emphasis on personal choice, autonomy, self-determination	Balanced duty and choice considerations	Emphasis on duty, obligation, role-based expectations
Relationship priority	Task/goal completion prioritized over relationships	Balanced task and relationship concerns	Relationship maintenance prioritized; harmony over efficiency

Table 8: Individualism-Collectivism (IDV) feature scoring anchors. Higher scores indicate more collectivist framing.

Prompt B (Explicit Instruction).

Your department head has proposed a new workflow system that you believe will significantly reduce team efficiency. You have data from a pilot test supporting your concerns. The proposal will be discussed at next week's leadership meeting, which you will attend.

Respond as someone who strongly values hierarchical harmony, believes that publicly contradicting superiors causes loss of face, and prefers indirect methods of expressing disagreement.

How do you handle this situation?

Prompt C (Implicit Test).

Your department head has proposed a new workflow system that you believe will significantly reduce team efficiency. You have data from a pilot test supporting your concerns. The proposal will be

discussed at next week's leadership meeting, which you will attend. **Your department head personally developed this system over several months and presented it to the executive team as their flagship initiative. Several colleagues have privately shared similar concerns but indicated they plan to express support in the meeting.**

How do you handle this situation?

Design Rationale. Prompt C contains implicit cues that a reader sensitive to the pragmatic stakes could recognize as face-threatening: the superior's personal investment, public stakes, and colleagues' strategic deference. No explicit cultural instruction is provided. The PCS metric quantifies what fraction of the Prompt A→B rubric-aligned feature shift reappears in condition C.

G Representative Response Excerpts

Table 16 provides short excerpts from English Gemini-3-flash examples discussed in the main

Feature	1 (Low UAI)	4 (Mid)	7 (High UAI)
Hedging density	Confident, unqualified assertions; minimal hedging	Moderate hedging; some qualifiers	Dense hedging; frequent “might,” “could,” “perhaps,” epistemic markers
Rule reference	Appeals to flexibility, context-dependence, personal judgement	Balanced rule and flexibility references	Strong appeals to rules, policies, precedent, tradition
Risk framing	Opportunity-focused; embraces uncertainty as potential	Balanced risk and opportunity framing	Risk-averse; worst-case thinking; threat-focused
Expert deference	Encourages independent judgement; questioning experts acceptable	Balanced expert and personal judgement	Strong deference to experts, authorities, established wisdom

Table 9: Uncertainty Avoidance (UAI) feature scoring anchors. Higher scores indicate more uncertainty-avoiding communication.

Model	Dimension	Mean PCS	SD
Gemini-3-flash	PDI	0.414	0.124
	IDV	0.102	0.081
	UAI	0.206	0.076
Grok-4.1-fast	PDI	0.236	0.129
	IDV	0.106	0.056
	UAI	0.176	0.069
Mimo-V2-flash	PDI	0.373	0.148
	IDV	0.135	0.088
	UAI	0.138	0.086
Ministral-8B	PDI	0.219	0.175
	IDV	0.132	0.069
	UAI	0.111	0.083

Table 10: Stable-only PCS by model and cultural dimension. UAI rows exclude the unstable hedging-density ratios for all models, and Ministral’s PDI mean excludes one unstable communication-channel cell.

text. They are included to make the qualitative interpretation of the scores more concrete.

H Feature-Level PCS Rankings

Table 17 ranks all 12 pragmatic features by the median across the five pooled-model language cells. Section 4.2 instead reports means across 20 model-language cells per feature, so the values and first two ranks need not coincide.

I Statistical Test Details

I.1 Primary Cross-Linguistic Tests (RQ1)

Primary cross-linguistic tests operate on matched scenario-feature means and use Friedman tests rather than pooled-observation ANOVA.

Model	Language	Mean PCS	SD
Gemini-3-flash	German	0.237	0.151
	English	0.294	0.169
	Hindi	0.215	0.169
	Nepali	0.266	0.226
	Urdu	0.206	0.114
Grok-4.1-fast	German	0.172	0.121
	English	0.203	0.122
	Hindi	0.143	0.093
	Nepali	0.162	0.106
	Urdu	0.182	0.098
Mimo-V2-flash	German	0.179	0.115
	English	0.221	0.164
	Hindi	0.195	0.121
	Nepali	0.269	0.257
	Urdu	0.246	0.107
Ministral-8B	German	0.149	0.065
	English	0.126	0.070
	Hindi	0.110	0.098
	Nepali	0.215	0.186
	Urdu	0.187	0.166

Table 11: Stable-only PCS by model and language. Most rows summarize 11 stable features; Ministral-Nepali summarizes 10 because two cells are unstable.

I.2 Context Sensitivity by Language (RQ2)

Paired *t*-tests compared matched scenario-feature Prompt A and Prompt C means within each language.

I.3 Hindi-Urdu Divergence (RQ4)

Primary Hindi-Urdu analysis uses a paired test on matched scenario-feature Prompt A means.

- Hindi mean LDI: 5.24
- Urdu mean LDI: 5.22
- $t = 0.96, p = 0.339$

Model	PCS	Shift Rec.	$\bar{A}$	$\bar{B}$	$\bar{C}$
Gemini-3-flash	0.244	19.0%	5.24	6.76	5.53
Mimo-V2-flash	0.222	17.3%	5.17	6.61	5.42
Grok-4.1-fast	0.172	15.3%	5.00	6.67	5.26
Ministral-8B	0.157	13.6%	5.03	6.38	5.21

Table 12: Stable-only model summary. PCS and shift recovery are defined as in Table 2; $\bar{A}$, $\bar{B}$, and $\bar{C}$ are means over the same stable model-language-dimension-feature cells.

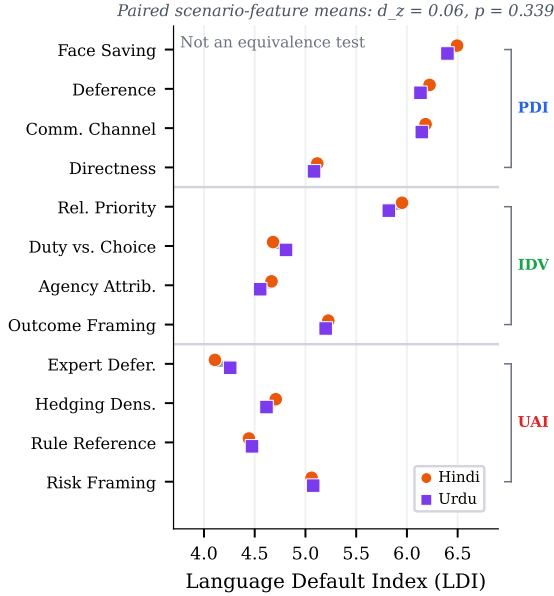


Figure 6: Hindi-Urdu baseline comparison across all 12 features. Differences are small overall, but this figure should not be interpreted as a formal equivalence test.

- Cohen’s $d_z = 0.06$ (negligible effect)
- $n = 240$ matched scenario-feature pairs

The non-significant divergence ($p = 0.339$, $d_z = 0.06$) shows no reliable Hindi-Urdu baseline separation in this controlled setup. This should not be interpreted as a formal equivalence test, nor as evidence that Hindi and Urdu are pragmatically identical in general.

J Further Analyses

This appendix collects descriptive interpretations of the main patterns. These analyses are intended to explain the released results, not to establish new causal claims.

J.1 Dimension Asymmetry: What Models Detect vs. What They Miss

Not all cultural dimensions transfer equally from explicit to implicit cueing. Under the release-

primary stable-only summary, Power Distance scenarios elicit the strongest implicit adaptation (mean $PCS = 0.299$), Individualism-Collectivism the weakest (0.120), and Uncertainty Avoidance sits in between (0.161) once unstable denominators are excluded.

One plausible explanation for the Power Distance advantage is the surface salience of hierarchical markers. PDI scenarios contain recognisable cues such as seniority relations, public versus private settings, and face-threatening stakes. These cues have clear lexical and structural correlates. A scenario about disagreeing with a senior manager in a public meeting contains multiple redundant signals that point toward indirect, deferential behaviour.

The main UAI caveat is *hedging_density*. For this feature, Prompt B scores are lower than Prompt A scores in all five languages, so the explicit gap is negative and the resulting PCS ratio is unstable. The raw *hedging_density* diagnostics remain negative in every language ($de = -0.14$, $en = -0.06$, $hi = -0.38$, $ne = -0.68$, $ur = -0.40$), but these cells are excluded from the stable-only aggregate. The remaining UAI features are positive, with *risk_framing* (0.210) and *expert_deference* (0.158) showing modest implicit transfer.

The weakness of Individualism-Collectivism transfer persists across all languages. Stable-only IDV means remain low even in English, and the strongest IDV feature, *relationship_priority*, reaches only 0.186. This pattern suggests that shifts in agency attribution, outcome framing, and duty-versus-choice orientation are harder for the tested endpoints to modulate reliably without explicit prompting.

J.2 Hindi-Urdu Baseline Comparison

The Hindi-Urdu comparison provides a diagnostic paired comparison for asking whether baseline pragmatic behaviour separates when two languages share substantial grammatical structure but differ in script, lexicon, and register. If those language-associated differences were sufficient to shift model defaults in our setup, we would expect systematically different pragmatic defaults when prompts are presented in Hindi versus Urdu.

We instead find minimal divergence. The primary paired scenario-feature test yields Hindi mean $LDI = 5.24$, Urdu mean $LDI = 5.22$, $t = 0.96$, $p = 0.339$, $d_z = 0.06$. This trivial difference holds across all twelve pragmatic features and all three

Dimension	Feature	German	English	Hindi	Nepali	Urdu
IDV	Agency attribution	4.17 $\pm$ 0.88	4.08 $\pm$ 0.80	4.67 $\pm$ 0.93	4.73 $\pm$ 0.94	4.55 $\pm$ 0.82
	Duty vs. choice	4.07 $\pm$ 0.73	3.95 $\pm$ 0.67	4.68 $\pm$ 0.71	4.81 $\pm$ 0.77	4.81 $\pm$ 0.75
	Outcome framing	4.65 $\pm$ 0.93	4.37 $\pm$ 0.85	5.23 $\pm$ 0.90	5.28 $\pm$ 0.95	5.20 $\pm$ 0.84
	Relationship priority	5.29 $\pm$ 0.89	5.05 $\pm$ 0.87	5.95 $\pm$ 0.76	5.98 $\pm$ 0.83	5.82 $\pm$ 0.80
PDI	Communication channel	6.18 $\pm$ 0.91	6.29 $\pm$ 0.76	6.18 $\pm$ 0.85	6.15 $\pm$ 0.88	6.15 $\pm$ 0.88
	Deference	5.66 $\pm$ 0.71	5.82 $\pm$ 0.77	6.22 $\pm$ 0.62	6.08 $\pm$ 0.73	6.13 $\pm$ 0.67
	Directness	4.86 $\pm$ 0.72	5.06 $\pm$ 0.87	5.12 $\pm$ 0.88	4.95 $\pm$ 0.92	5.08 $\pm$ 0.87
	Face-saving	6.31 $\pm$ 0.46	6.44 $\pm$ 0.44	6.49 $\pm$ 0.45	6.36 $\pm$ 0.57	6.40 $\pm$ 0.49
UAI	Expert deference	3.47 $\pm$ 1.55	3.65 $\pm$ 1.47	4.11 $\pm$ 1.40	4.21 $\pm$ 1.41	4.26 $\pm$ 1.38
	Hedging density	4.47 $\pm$ 0.74	4.69 $\pm$ 0.71	4.71 $\pm$ 0.81	4.66 $\pm$ 0.83	4.62 $\pm$ 0.80
	Risk framing	4.68 $\pm$ 1.34	4.88 $\pm$ 1.25	5.06 $\pm$ 1.16	4.94 $\pm$ 1.30	5.08 $\pm$ 1.17
	Rule reference	4.07 $\pm$ 1.21	4.24 $\pm$ 1.15	4.44 $\pm$ 1.03	4.45 $\pm$ 1.12	4.47 $\pm$ 1.09

Table 13: Language Default Index (LDI) scores for all language-feature combinations. Values are mean $\pm$ SD. Higher IDV scores indicate more collectivist defaults; higher PDI scores indicate more hierarchical defaults; higher UAI scores indicate more uncertainty-avoiding defaults.

Model	Hindi LDI	Urdu LDI	HUD
Mimo-V2-flash	5.30	5.19	0.110
Ministral-8B	5.21	5.15	0.055
Grok-4.1-fast	5.09	5.13	0.038
Gemini-3-flash	5.36	5.38	0.026

Table 14: Hindi-Urdu Divergence (HUD) by model. HUD = absolute difference in mean LDI. All values represent negligible practical divergence ($< 3\%$ of scale range).

cultural dimensions. The largest observed feature gap is expert_deference (HUD = 0.150), followed by relationship_priority (0.130), both still small relative to the 1–7 scale.

This finding does not settle the relative roles of linguistic structure and cultural association, and it is not a formal equivalence test. It shows only that presenting otherwise matched scenarios in Hindi versus Urdu was not sufficient to produce large baseline differences in this controlled prompt setup.

J.3 Alternative Explanations

Four potential confounds warrant consideration. First, the low PCS scores for South Asian languages might reflect language-resource differences rather than a pragmatic cueing issue. However, this explanation would predict substantially higher implicit transfer in English. We do not observe that pattern: stable-only PCS is of comparable magnitude across English (0.215), German (0.181), Hindi (0.167), Nepali (0.211), and Urdu (0.208).

Second, our Prompt C design deliberately avoided culturally indexical markers such as names, locations, or explicit cultural references. This makes the implicit condition sparser than many

Dim.	Feature	Hindi	Urdu	HUD
IDV	Agency attribution	4.67	4.55	0.112
IDV	Duty vs. choice	4.68	4.81	0.128
IDV	Outcome framing	5.23	5.20	0.026
IDV	Relationship priority	5.95	5.82	0.130
PDI	Communication channel	6.18	6.15	0.037
PDI	Deference	6.22	6.13	0.089
PDI	Directness	5.12	5.08	0.032
PDI	Face-saving	6.49	6.40	0.095
UAI	Expert deference	4.11	4.26	0.150
UAI	Hedging density	4.71	4.62	0.091
UAI	Risk framing	5.06	5.08	0.016
UAI	Rule reference	4.44	4.47	0.030
Overall		5.24	5.22	0.02

Table 15: Feature-level Hindi-Urdu divergence. Largest divergence (expert_deference, HUD = 0.150) remains small in absolute terms. Primary paired test on matched scenario-feature means: $t = 0.96$, $p = 0.339$, $d_z = 0.06$.

real-world interactions. We consider this a methodological strength for the present diagnostic: including demographic markers would conflate pragmatic cueing with stereotype activation. By testing whether models respond to situational cues alone, we isolate response movement associated with those cues.

Third, our use of Hofstede’s cultural dimensions invites scrutiny. The framework originates from national-level survey data and has been critiqued for essentialising culture (Mc Sweeney, 2002). We acknowledge these limitations but retain the framework because it remains widely used in computational work and still yields internally structured asymmetries in our data.

Fourth, one might argue our findings reflect a

Scenario	Prompt A excerpt	Prompt B excerpt	Prompt C excerpt
PDI workplace disagreement	“I’ve found some significant bottlenecks that I wanted to share with you first so we can address them before the leadership meeting.”	“I would frame my concerns as a request for their wisdom.”	“Never blindsides a leader with negative data in a public forum ... Your first move must be a private, one-on-one meeting.”
IDV family loan request	“I need a few days to look at my budget and think it over.”	“Of course, I will help you. We are family, and what is mine is ours.”	“I really appreciate you coming to me with this ... but I need to be honest about the risk.”
UAI procedure deviation	“There is an opportunity for team improvement, but bypassing established procedures can create risks.”	“Our documented processes are not merely suggestions ... how we achieve a result is just as important as the result itself.”	“A good result achieved through a non-compliant process is a liability, not a success.”

Table 16: Representative response excerpts from English Gemini-3-flash. The PDI and UAI examples show partial recovery of hierarchy-sensitive and rule/risk-oriented strategies under implicit cueing, while the IDV example shows that Prompt C moves only partway toward the collectivist behavior seen in Prompt B.

Rank	Feature	Dim.	Median PCS
1	Face-saving	PDI	0.365
2	Deference	PDI	0.358
3	Communication channel	PDI	0.335
4	Relationship priority	IDV	0.212
5	Directness	PDI	0.208
6	Risk framing	UAI	0.205
7	Expert deference	UAI	0.178
8	Duty vs. choice	IDV	0.117
9	Outcome framing	IDV	0.117
10	Rule reference	UAI	0.114
11	Agency attribution	IDV	0.068
12	Hedging density	UAI	unstable

Table 17: Feature-level implicit sensitivity ranked by median stable PCS across the five pooled-model language cells. Hedging_density is listed as unstable because its explicit gap is negative in all five languages.

Dimension	χ^2	p	W	n blocks
PDI	47.41	1.25×10^{-9}	0.148	80
IDV	223.00	4.25×10^{-47}	0.697	80
UAI	73.98	3.28×10^{-15}	0.231	80

Table 18: Primary matched-item Friedman tests for cross-linguistic Prompt A differences. Legacy pooled-observation ANOVA results are retained in the released supplementary statistics but are not the primary inferential basis of the paper.

general explicit-versus-implicit gap rather than anything specific to cultural pragmatics. The dimension asymmetry is not what we would expect under a completely uniform gap, though it does not identify the cause. Instead, we observe a clear Power Distance advantage, persistently weak IDV transfer, and one feature-level UAI failure mode in hedging_density. Models can respond to some implicit contextual cues more reliably than others.

Lang.	$\bar{A}$	$\bar{B}$	$\bar{C}$	t	p	d_z
German	4.82	6.40	5.09	-7.95	7.21×10^{-14}	0.513
English	4.88	6.45	5.16	-7.95	7.25×10^{-14}	0.513
Hindi	5.24	6.46	5.42	-5.40	1.60×10^{-7}	0.349
Nepali	5.22	6.30	5.43	-6.39	8.69×10^{-10}	0.412
Urdu	5.22	6.40	5.44	-6.80	8.48×10^{-11}	0.439

Table 19: Primary within-language context-sensitivity tests on matched scenario-feature means. All languages show significant A→C shifts, but the corresponding effect sizes remain moderate.

J.4 Error Analysis

We identify three recurring patterns that account for the majority of anomalous PCS values in our data. Together, these cases show where the metric or the tested endpoints behave less stably.

Negative UAI-PCS values: implicit cues that backfire. Of the 240 per-model feature cells in our design (4 models $\times$ 5 languages $\times$ 12 features), 20 cells (8.3%) receive a negative_explicit_gap classification, meaning that the explicitly prompted condition (Prompt B) scores *lower* than the neutral baseline (Prompt A). All 20 of these cells belong to a single feature, hedging_density, discussed further below. Beyond hedging_density, a few stable model-language-feature cells occasionally dip slightly below zero—for instance, communication_channel for Grok-4.1-fast in German (PCS = -0.059) and directness for Ministral-8B in Hindi (PCS = -0.015)—but these are small in magnitude and do not recur systematically across languages. The concentration of negative values in one feature, rather than their dispersal across many, is more consistent with a feature-specific failure mode than with general instability across the full rubric.

One untested possibility is that assistant-style response preferences favour confident, concise answers over heavily qualified ones, but we cannot distinguish training, alignment, decoding, prompting, or judge-rubric explanations. The observable pattern is simpler: when models are explicitly instructed to adopt high-uncertainty-avoidance norms (Prompt B), which our rubric associates with more hedging and cautious language, the Prompt B hedging score often falls below baseline. For example, in Nepali the mean Prompt A hedging_density score is 4.66, but the explicitly prompted Prompt B score drops to 4.27, yielding a negative explicit gap ($\Delta_{AB} = -0.39$). Because the explicit reference shift is inverted, hedging_density cannot support an interpretable positive PCS value.

High-variance model-language outliers. Not all model-language cells exhibit stable pragmatic behaviour. Mimo-V2-flash on Nepali produces the highest within-cell standard deviation among all model-language pairs for stable PCS values ($SD = 0.257$, $mean = 0.269$, $n = 11$ stable features), followed by Gemini-3-flash on Nepali ($SD = 0.226$, $mean = 0.266$, $n = 11$ stable features). For comparison, the same models on German yield $SD = 0.115$ and $SD = 0.151$, respectively. This elevated variance in Nepali is not attributable to a single outlying feature: at the released model-language summary level, Mimo-V2-flash on Nepali ranges from $PCS = -0.035$ on rule_reference to 0.719 on face_saving, a spread of 0.754.

Within our five-language sample, Nepali shows higher within-cell variance; whether this relates to language-resource level, prompts, scoring, or model behaviour remains untested. The same model-language setting can show slight reversals on some features (for example, Mimo-V2-flash on Nepali has $PCS = -0.035$ on rule_reference) and strong adaptation on others (face_saving reaches 0.719). This inconsistency is itself informative: in this dataset, Nepali performance is not uniformly low, but it is high-variance across features within the same language.

Hedging density as a systematic failure mode. Hedging_density is the only feature in our design for which PCS is negative in every language: $de = -0.14$, $en = -0.06$, $hi = -0.38$, $ne = -0.68$, $ur = -0.40$. Across all 20 model-language cells for this feature, none achieves a stable positive PCS, and the feature is excluded entirely from the stable-only aggregate. Across the five language-level ag-

gregates, the mean raw PCS for hedging_density is -0.33 .

The pattern is consistent across languages but varies in severity. In all five languages, the Prompt B mean (explicitly prompted high-UAI) is lower than the Prompt A mean (neutral baseline), producing a negative Δ_{AB} : $de = -0.53$, $en = -0.62$, $hi = -0.29$, $ne = -0.39$, $ur = -0.43$. Meanwhile, the implicit condition (Prompt C) typically produces hedging scores that are *higher* than baseline, moving toward the high-UAI rubric direction but doing so against a denominator that is itself inverted. The result is a PCS ratio that is mathematically negative and substantively uninterpretable as pragmatic competence.

This failure is most severe in Nepali ($PCS = -0.68$), where the implicit condition score ($c = 4.92$) substantially exceeds the explicit condition score ($b = 4.27$), while the baseline ($a = 4.66$) sits between them. Because the explicit condition itself does not create the intended reference shift, the PCS metric cannot capture the Prompt C movement cleanly. We flag hedging_density as a case where the evaluation framework’s assumption of a positive explicit gap does not hold, and recommend that future work treat this feature with separate analytical tools that do not depend on a well-behaved denominator.

K Human Pairwise-Preference Study

We conducted a descriptive human pairwise-preference study with native-speaker author/collaborator raters rather than a recruited representative participant sample. For each language, the planned design included 24 A-vs-C and 24 B-vs-C comparisons on a fixed 24-scenario subset. The released artifacts contain one finalized comparison sheet per language, yielding 120 completed A-vs-C comparisons and 119 completed B-vs-C comparisons overall; one Urdu B-vs-C item was left blank. Raters compared each pair in randomized, blinded presentation and judged which complete response better fit the scenario’s social and cultural context overall, with a “no meaningful difference” option. This study was not designed as a representative human baseline and does not directly validate PCS, because raters did not score the 12 pragmatic features.

For A-vs-C comparisons, aggregate preferences were nearly balanced once ties were excluded (36 C wins vs. 34 A wins, with 50 ties; two-sided ex-

Table 20: Human pairwise-preference results by language. Totals are descriptive rather than confirmatory because the release contains one finalized sheet per language and comparisons are clustered by scenario and language.

Lang	A vs C				B vs C			
	A	C	Tie	Total	B	C	Tie	Total
German (de)	9	4	11	24	3	7	14	24
English (en)	11	11	2	24	5	17	2	24
Hindi (hi)	1	5	18	24	2	11	11	24
Nepali (ne)	11	11	2	24	8	10	6	24
Urdu (ur)	2	5	17	24	6	9	8	23
Total	34	36	50	120	24	54	41	119

act sign test $p \approx .905$). For B-vs-C comparisons, decisive choices leaned toward C (54 C wins vs. 24 B wins, with 41 ties; two-sided exact sign test $p \approx .0009$, Wilson 95% CI [0.583, 0.784]). Because the release contains one finalized sheet per language and comparisons are clustered by scenario and language, these totals and tests should be read as descriptive patterns rather than confirmatory inference.

L Data Availability

The release includes the 60 scenarios and translations, 20 raw response files, 20 score files, canonical derived statistics, publication figures, human preference-study materials, and judge sanity-check summaries. The scored corpus contains 14,400 prompt/sample entries, of which 14,270 contain usable feature scores (57,080 feature-level observations) and 130 contain empty score objects because all judge outputs failed parsing or validation.

Response_validity is optional in the public score files and is present for 11,719 of the 14,270 feature-scored entries (82.1% coverage); primary statistics therefore retain all entries with usable feature scores rather than filtering on response_validity. The public bundle does not include the raw GPT-4o proxy scores used in judge selection, the raw candidate-judge trial outputs, or the original worksheet used to select the 24-scenario human preference subset.

The released bundle includes the scenarios, model responses, derived scoring files, analysis code, and generated statistics needed to inspect and rerun the released analyses, subject to the provenance omissions noted above.

The submitted archive was rebuilt without platform-specific metadata files or Python bytecode caches and verified with `unzip -t`. Its SHA-256 checksum is 8147d809d48bc8fe

51f0d2cfa219455b74b17d78cdf1a4c0b822be3003d6bb74.