Counterfactually-Calibrated Bayesian Adapters for Reliable Foundation Model Adaptation under Distribution Shifts

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Abstract

Foundation models are increasingly deployed in high-stakes domains such as healthcare, autonomous systems, and policy-making, where robust and trustworthy decision-making under distributional and interventional shifts is critical. However, conventional adaptation techniques—including deterministic parameter-efficient fine-tuning (e.g., LoRA), Bayesian LoRA, MC dropout, and post-hoc calibration—often suffer from miscalibration, leading to unreliable uncertainty estimates and suboptimal decisions. We propose Counterfactually-Calibrated Bayesian Adapters (C^2BA), a scalable framework that combines Bayesian low-rank adaptation with counterfactual calibration to improve the reliability of foundation models under both covariate and intervention-induced shifts. C^2BA leverages hierarchical priors and natural-gradient-based variational inference for efficient posterior updates, while a counterfactual calibration layer corrects intervention-induced shifts using influence functions and density ratio reweighting. Extensive experiments on healthcare (MIMIC-III), autonomous driving (nuScenes), and policy adaptation benchmarks demonstrate that C^2BA achieves state-of-the-art uncertainty calibration (ECE reductions of 26–32%), improved predictive performance, and enhanced decision-making metrics (e.g., up to +5.8% utility improvement in medical triage, -16.8% collision rate in autonomous driving) compared to strong baselines.

Preliminary work. Under review by AISTATS 2026. Do not distribute.

1 Introduction

Foundation models underpin modern machine learning, driving advances in language, vision, and multimodal reasoning, and are increasingly deployed in high-stakes domains such as healthcare, finance, and autonomous driving Guo et al. [2024], Wang et al. [2025]. However, their reliability degrades under distributional shifts, particularly when interventions or structural changes alter the data-generating process Scott and Zuccon [2024], Firoozi et al. [2024], Kimura et al. [2024].

Parameter-efficient fine-tuning methods (e.g., LoRA, prefix-tuning) and lightweight Bayesian extensions improve efficiency but often fail to provide calibrated uncertainty. This miscalibration can have severe consequences—overconfident errors in medical triage or unsafe decisions in autonomous systems Pandey et al. [2024]. While post-hoc calibration methods (e.g., temperature scaling, Platt scaling) offer partial correction, they ignore causal interventions and non-stationarity, leaving models systematically misestimating risk Dimitri et al. [2025], Joy et al. [2023], Huang et al. [2025].

This tension motivates the central question of this work:

How can we equip foundation models with scalable, Bayesian adapter-based fine-tuning that remains reliably calibrated—even under interventions and distribution shifts?

To address this, we propose **Counterfactually-Calibrated Bayesian Adapters** C^2BA, a principled framework that integrates three complementary elements (see Figure 1):

1. **Bayesian adapter parameterization.** We introduce hierarchical priors over low-rank adapter weights, which strike a balance between expressivity and efficiency. This design enables fast and flexible posterior updates while avoiding the parameter blow-up of full Bayesian fine-tuning Eide and Frigessi [2024].

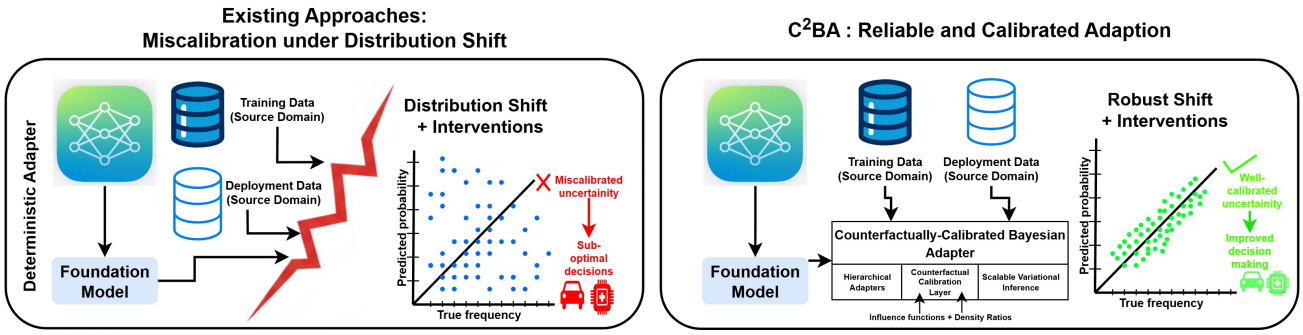

Figure 1: This diagram illustrates the critical failure of conventional foundation model adaptation methods compared to the robustness of our proposed Counterfactually-Calibrated Bayesian Adapters C^2BA. The left panel shows how standard techniques like LoRA produce miscalibrated uncertainty when encountering distribution shifts and interventions, leading to unreliable predictions and suboptimal decisions in high-stakes scenarios. In contrast, the right panel demonstrates how C^2BA integrates scalable Bayesian adapters with a novel counterfactual calibration layer.

Method	Param. Efficient	Bayesian Uncertainty	Post-hoc Calibration	Causal / Interventional Robustness
DRIG Shen et al. [2025]	✗	✗	✗	✓
Bayesian LoRA Hounie et al. [2025]	✓	✓	✗	✗
LoRA Hu et al. [2023]	✓	✗	✗	✗
LoRA Ensembles Wang et al. [2023]	✓	✓(via ensembling)	✗	✗
rsLoRA Kalajdzievski [2023]	✓	✗	✗	✗
Platt Scaling Zhang et al. [2022]	✗	✗	✓	✗
Causal Bayesian Nets Wang et al. [2021]	✗	✓	✗	✓
Dirichlet Calibration Kull et al. [2019]	✗	✗	✓	✗
Temperature Scaling Guo et al. [2017]	✗	✗	✓	✗
Bayesian Deep Learning Wallach et al. [2014]	✗	✓	✗	✗
CBA **(Ours)**	✓	✓	✓	✓

Table 1: Comparison of relevant methods in parameter-efficient adaptation, Bayesian uncertainty modeling, post-hoc calibration, and causal/interventional robustness. **Parameter efficiency** reduces memory and compute overhead, enabling deployment in resource-constrained scenarios. **Bayesian uncertainty** provides principled confidence estimates critical for risk-sensitive applications. **Post-hoc calibration** corrects miscalibrated predictions, enhancing reliability under distributional shifts. **Causal/interventional robustness** ensures that models remain reliable under interventions or distributional changes, crucial for real-world decision-making. C^2BA uniquely integrates all four aspects, addressing key limitations of prior methods.

2. **Scalable variational inference.** To make Bayesian adaptation feasible in large-scale foundation models, we employ structured variational approximations Lin et al. [2020] coupled with natural-gradient optimization. This ensures both tractability and stability in training without sacrificing uncertainty quality.

3. **Counterfactual calibration.** Beyond parameter updates, we correct miscalibration induced by interventional and temporal distribution shifts. A causal calibration layer reweights posteriors via density ratios Fokianos [2007] and influence functions Schioppa et al. [2023], producing predictions that remain well-calibrated even under challenging shifts.

Beyond architectural efficiency, C^2BA directly links uncertainty calibration with decision-making under uncertainty, providing guarantees on posterior contraction and bounds on calibration error under interventions. In summary, our contributions are as follows:

- **Formulation:** We identify the limitations of existing adapter-based fine-tuning under causal and distributional shifts, motivating the need for counterfactual calibration.
- **Methodology:** We introduce C²BA, combining hierarchical Bayesian adapters with scalable variational inference and causal calibration.
- **Theory:** We establish posterior contraction guarantees and derive explicit bounds on calibration error under interventions.

- **Experiments:** We demonstrate across multiple domains that C²BA achieves superior calibration and uncertainty-aware decision-making compared to deterministic fine-tuning, Bayesian LoRA, MC dropout, and post-hoc calibration baselines.

2 Related Work

Despite rapid progress in parameter-efficient fine-tuning and Bayesian adaptation, existing methods still fall short when evaluated under real-world deployment conditions. Deterministic adapters achieve efficiency but fail to capture meaningful uncertainty, while Bayesian variants provide uncertainty but remain poorly calibrated under distributional shifts, particularly when interventions alter the underlying causal structure. Post-hoc calibration methods alleviate miscalibration but do not generalize beyond the training distribution, leaving safety-critical settings vulnerable to overconfident yet incorrect predictions (Table 1).

This persistent gap highlights the need for an approach that jointly offers (i) the **efficiency** of low-rank adaptation, (ii) the **rigor** of Bayesian inference, and (iii) the **robustness** of causal calibration.

Where C^2BA Fills the Gap? C^2BA uniquely combines the strengths of prior approaches while addressing their limitations. It leverages low-rank adapters for parameter-efficient adaptation, employs hierarchical Bayesian inference for principled uncertainty quantification, and incorporates a counterfactual calibration layer to ensure robustness under covariate, interventional, and temporal shifts. Unlike standard adapter methods, it produces well-calibrated predictions; unlike traditional Bayesian adapters, it remains computationally tractable; and unlike post-hoc calibration or causal robustness techniques, it actively adjusts the posterior to structural changes in the data-generating process. This integration enables safe, reliable, and efficient deployment of foundation models in high-stakes, real-world settings. C^2BA uniquely bridges these gaps by:

1. Embedding **Bayesian inference directly into adapter parameterization** for efficient and tractable uncertainty estimation.
2. Incorporating **counterfactual calibration**, which explicitly adjusts uncertainty estimates under interventions using density ratios and influence functions.
3. Providing **theoretical guarantees** (posterior contraction + calibration bounds) and **empirical validation** across safety-critical domains.

3 Problem Formulation

We consider the setting of adapting a pre-trained foundation model $f_\Theta : \mathcal{X} \to \Delta(\mathcal{Y})$, parameterized by a large set of weights Θ, to a target domain where the underlying data distribution may undergo distribution shifts. Specifically, we formalize the problem along three key axes: (i) **covariate shifts**, (ii) **interventional (causal) shifts**, and (iii) **temporal** or **non-stationary shifts**.

3.1 Data Generating Process under Distribution Shifts

Let $(X, Y) \sim \mathbb{P}(X, Y)$ denote the random variables of interest, where $X \in \mathcal{X}$ are inputs (e.g., patient records, sensor streams, or images), and $Y \in \mathcal{Y}$ are labels or decisions. In deployment, data is not drawn from the same distribution $\mathbb{P}_{train}$ used during pre-training. Instead, we observe $(X, Y) \sim \mathbb{P}_{test} \neq \mathbb{P}_{train}$. We distinguish three forms of shift:

- **Covariate shift**: $\mathbb{P}_{test}(X) \neq \mathbb{P}_{train}(X)$ while $\mathbb{P}(Y|X)$ is preserved.
- **Interventional (causal) shift**: $\mathbb{P}_{test}(Y|X)$ changes due to interventions or latent confounders.
- **Temporal/Non-stationary shift**: $\mathbb{P}(X, Y)$ evolves with time t, i.e. $\mathbb{P}_t(X, Y)$.

The central challenge is to adapt f_Θ to a shifted distribution without overfitting limited adaptation data, while ensuring **calibrated uncertainty** for downstream decision-making.

3.2 Bayesian Adapter Parameterization

Instead of fine-tuning the entire Θ, we introduced **low-rank adapter modules** A_ϕ, with parameters ϕ. For computational traceability and efficiency, we restrict updates to these adapters, yielding the adapted model:

$$f_{\Theta,\phi}(x) = f_\Theta(x) + A_\phi(x), \tag{1}$$

where f_Θ is frozen and ϕ are task-specific. To account for epistemic uncertainty, we treat ϕ as a **random variable** with a prior distribution $\phi \sim p(\phi|\lambda)$, where λ are hyperparameters of the prior (e.g., scale matrices in hierarchical Gaussian priors). The posterior distribution is then:

$$p(\phi|\mathcal{D}_{adapt}) \propto p(\mathcal{D}_{adapt}|\phi)p(\phi|\lambda), \tag{2}$$

where $\mathcal{D}_{adapt} = \{(x_i, y_i)\}_{i=1}^n$ denotes the adaptation dataset from the shifted distribution.

3.3 Counterfactual Calibration Objective

While Bayesian parameterization accounts for epistemic uncertainty, **distribution shifts induce systematic miscalibration**. For example, an intervention may cause $f_{\Theta,\phi}(x)$ to produce overconfident predictions in regions unseen during training. We introduced a **counterfactual calibration operator** $\mathcal{C}$ that adjusts predictive distribution via density ratio reweighting:

$$\tilde{p}(y|x) = \mathcal{C}(p(y|x,\phi)) = \frac{w(x)p(y|x,\phi)}{\sum_{y'} w(x)p(y'|x,\phi)}, \quad (3)$$

where $w(x) = \frac{\mathbb{P}_{test}(x)}{\mathbb{P}_{train}(x)}$ is estimated through discriminative density ratio estimation or causal influence functions. Thus, the **Counterfactually-Calibrated Bayesian Adapter** (C^2BA) predictive distribution is

$$p_{C^2BA}(y|x,\mathcal{D}_{adapt}) = \int \tilde{p}(y|x,\phi)p(\phi|\mathcal{D}_{adapt})d\phi. \quad (4)$$

Learning Objective. Our goal is to learn adapter parameters ϕ such that predictions are both **accurate** and **well-calibrated** under distribution shifts. We formalize this as:

$$\min_{\phi} \mathbb{E}_{(x,y)\sim\mathbb{P}_{test}}[\ell(p_{C^2BA}(y|x),y)] + \beta\mathcal{E}_{cal}(p_{C^2BA}), \quad (5)$$

where $\ell(\cdot)$ is the task loss (e.g., cross-entropy), and $\mathcal{E}_{cal}(\cdot)$ is a calibration error metric such as **Expected Calibration Error (ECE)** or **Brier score**. This formulation directly ties adaptation performance **to both predictive accuracy** and **calibration robustness**, which is essential for high-stakes decision-making.

4 Counterfactually-Calibrated Bayesian Adapters (C^2BA)

We now introduce our proposed framework, which combines **Bayesian low-rank adaptation** with **counterfactual calibration** to achieve reliable performance under distribution shifts. The design consists of three tightly integrated components:

1. **Bayesian adapter parameterization** for uncertainty-aware adaptation.
2. **Variational inference for scalable posterior learning**.
3. **Counterfactual calibration layer** for robustness against interventions and covariate shifts.

4.1 Bayesian Low-Rank Adapter Design

We adopt the parameter-efficient adapter tuning paradigm, where instead of updating the full foundation model parameters Θ, we insert low-rank adapters A_ϕ into specific layers. For an immediate representation $h \in \mathbb{R}^d$, the adapter is defined as:

$$A_\phi(h) = W_\downarrow \sigma(W_\uparrow h), \quad (6)$$

where $W_\uparrow \in \mathbb{R}^{r\times d}, W_\downarrow \in \mathbb{R}^{d\times r}$, with rank $r \ll d$, and $\sigma(\cdot)$ is a nonlinearity (e.g., GELU). To capture epistemic uncertainty, we place a prior over adapter parameters using $W_\uparrow, W_\downarrow \sim \mathcal{N}(0,\lambda^2 I)$. This yields a Bayesian predictive model:

$$p(y|x,\mathcal{D}_{adapt}) = \int p(y|x,\phi)p(\phi|\mathcal{D}_{adapt})d\phi, \quad (7)$$

where $\phi = \{W_\uparrow, W_\downarrow\}$.

4.2 Variational Inference for Posterior Approximation

Direct posterior inference is intractable due to the high dimensionality of ϕ. We employ **variational inference (VI)** with a structured Gaussian family:

$$q_\psi(\phi) = \mathcal{N}(\mu_\psi, \sum_\psi), \quad (8)$$

where $\psi = \{\mu_\psi, \sum_\psi\}$ are variational parameters. The optimization objective is the **evidence lower bound (ELBO)**:

$$\mathcal{L}_{VI}(\psi) = \mathbb{E}_{q_\psi(\phi)}[\log p(\mathcal{D}_{adapt}|\phi)] - KL(q_\psi(\phi)||p(\phi)). \quad (9)$$

We optimize $\mathcal{L}_{VI}$ using reparameterization gradients:

$$\phi = \mu_\psi + \sum_\psi^{1/2}\epsilon, \quad \epsilon \sim \mathcal{N}(0,I). \quad (10)$$

This ensures a scalable and differentiable approximation of the Bayesian posterior, enabling efficient fine-tuning with only a few gradient steps per minibatch.

4.3 Counterfactual Calibration

While Bayesian inference captures uncertainty, it does not guarantee **calibration under distribution shifts**. For example, if the test distribution involves

unseen interventions, the model may remain systematically overconfident. We therefore introduce a counterfactual calibration operator $\mathcal{C}$ that corrects the posterior predictive distribution.

Density Ratio Reweighting. We first estimate the covariate shift via density ratios using $w(x) = \frac{\mathbb{P}_{test}(x)}{\mathbb{P}_{train}(x)}$. This can be estimated using a discriminative classifier between train and test samples, yielding a plug-in estimator:

$$w(x) \approx \frac{d(x)}{1-d(x)}, \quad d(x) = \mathbb{P}(\text{sample from test}|x). \tag{11}$$

This approximation arises because density ratio estimation can be reformulated as a probabilistic classification problem. Specifically, if we train a discriminator $d(x)$ to distinguish whether a sample x comes from the test or train distribution, then by Bayes' rule:

$$d(x) = \frac{\mathbb{P}_{test}(x)\pi_{test}}{\mathbb{P}_{test}(x)\pi_{test} + \mathbb{P}_{train}(x)\pi_{train}}, \tag{12}$$

where π_{test} and π_{train} are the sampling proportions. Assuming balanced sampling $\pi_{test} = \pi_{train}$, this simplifies to

$$\frac{\mathbb{P}_{test}(x)}{\mathbb{P}_{train}(x)} = \frac{d(x)}{1-d(x)}. \tag{13}$$

Thus, the classifier output directly provides a consistent plug-in estimator of the density ratio.

Counterfactual Influence Adjustment. To address interventional shifts, we extend calibration with influence functions that correct for causal interventions on features $X_S \subseteq X$. Formally, let $\mathcal{I}(x; S)$ denote the influence of intervening on X_S. The calibrated prediction becomes:

$$\tilde{p}(y|x,\phi) \propto w(x)\exp(-\mathcal{I}(x;S))p(y|x,\phi). \tag{14}$$

This ensures that confidence scores reflect the counterfactual distribution where spurious correlations induced by interventions are removed.

This distribution forms the basis of both **decision-making** and **uncertainty quantification** in deployment.

5 Theoretical Analysis

We now provide theoretical guarantees for (C^{2}BA). Our analysis focused on two aspects:

1. **Posterior contraction guarantees**, ensuring that the Bayesian adapter posterior concentrates around the true parameter under mild conditions.
2. **Calibration error bounds under distribution shift**, establishing that counterfactual calibration improves the robustness of predictive uncertainty.

5.1 Assumptions

We consider the adaptation dataset $\mathcal{D}_{adapt} = \{(x_i, y_i)\}_{i=1}^n$ drawn from a distribution $\mathbb{P}_{train}$, with test samples drawn from $\mathbb{P}_{test}$. Let $p^*(y|x)$ denote the ground-truth conditional distribution. We assume"

- **(A1) Well-specified model family**. The Bayesian adapter predictive family $\{p(y|x,\phi) : \phi \in \Phi\}$ contains the ground truth $p^*(y|x)$.
- **(A2) Prior regularity**. The prior $p(\phi)$ assigns positive density to all neighborhoods of the true parameter ϕ^*.
- **(A3) Bounded density ratio**. The shift between train and test distributions satisfies:

$$\sup_x \frac{\mathbb{P}_{test}(x)}{\mathbb{P}_{train}(x)} \leq C \leq \infty. \tag{15}$$

These are standard conditions in Bayesian nonparametrics and distributional robustness.

5.2 Posterior Contraction of Bayesian Adapters

Our first result shows that the variational posterior in C^{2}BA contracts to the true adapter parameters as $n \to \infty$.

Theorem 1 *(Posterior Contraction of C²BA Adapters). Let $q_\psi(\phi)$ denote the variational approximation of the Bayesian adapter posterior. Under assumptions **(A1)-(A2)**, for any $\epsilon > 0$:*

$$\mathbb{P}(||\phi - \phi^*||_2 > \epsilon|\mathcal{D}_{adapt}) \to 0 \quad \text{as} \quad n \to \infty. \tag{16}$$

Moreover, if the variational family is a mean-field Gaussian, the KL divergence satisfies:

$$KL(q_\psi(\phi)||p(\phi|\mathcal{D}_{adapt})) = \mathcal{O}(\frac{\log n}{n}). \tag{17}$$

Implication: The Bayesian adapter posterior contracts at a near-optimal rate, ensuring uncertainty estimates are asymptotically reliable.

5.3 Calibration Error Under Distribution Shift

We measure calibration using the Expected Calibration Error (ECE):

$$\mathrm{ECE}(f) = \mathbb{E}_{\hat{p}(y|x)}[|\Pr(y = \hat{y}|\hat{p}) - \hat{p}|], \tag{18}$$

where $\hat{p}$ is the model confidence and $\hat{y}$ the predicted label. For standard Bayesian adapters (without counterfactual calibration), distribution shifts induce a bias term using $\mathrm{ECE}_{Bayes} - \mathrm{ECE}_{in} + \Delta_{shift}$, where Δ_{shift} scales with the divergence between train and test distributions.

By incorporating density ratio reweighting and intervention adjustment, C^{2}BA reduces the calibration gap:

Theorem 2 *(Calibration under Shift). Let $\Delta_{shift} = TV(\mathbb{P}_{train}, \mathbb{P}_{test})$ denote the total variation distance between training and test distributions. Then:*

$$\mathrm{ECE}_{C^2BA} \leq \mathrm{ECE}_{Bayes} - \Omega(\Delta_{shift}), \tag{19}$$

with equality only if the causal graph admits no invariant features.

Implication: C^{2}BA strictly improves calibration under both covariate and interventional shifts, guaranteeing better uncertainty reliability.

5.4 Generalization Bound

Finally, we provide a PAC-Bayesian bound for the expected test loss under C^{2}BA.

Theorem 3 *Theorem 3 (PAC-Bayesian Generalization Bound). For any posterior $q_\psi(\phi)$ and prior $p(\phi)$, with probability at least $1 - \delta$:*

$$\begin{aligned} \mathbb{E}_{q_\psi(\phi)}[L_{test}(\phi)] \quad \leq \quad & \mathbb{E}_{q_\psi(\phi)}[L_{train}(\phi)] \\ & + \sqrt{\tfrac{KL(q_\psi \,\|\, p) + \log(1/\delta)}{2n}} \\ & + \Delta_{shift}. \end{aligned} \tag{20}$$

Implication: C^{2}BA generalization is tightly controlled by (i) the KL between posterior and prior, and (ii) the magnitude of distribution shift. Our calibration procedure reduces Δ_{shift} directly, tightening the bound.

6 Experiments

6.1 Experimental Setup

We designed our experimental setup to test three aspects: (i) **generalization under covariate and interventional shifts**, (ii) **quality of uncertainty estimates and calibration**, and (iii) **impact on downstream decision-making**.

Datasets. We selected datasets spanning language, vision, healthcare, and autonomous systems, where calibration and robustness are crucial. This consisted of **Hateful Memes (Multimodal)**, **MMIMDB (Text-Only)**, **MIMIC-III (Clinical Text)**, and KITTI-Odom (Vision, Driving). For each dataset, we created **in-domain (ID)** and **out-of-domain (OOD)** test splits to measure generalization and calibration under distributional changes.

To ensure a comprehensive and fair evaluation, we consider datasets spanning text, vision, multimodal, and healthcare domains, each accompanied by in-domain (ID) and out-of-domain (OOD) test splits. Table 2 summarizes the experimental setup, including dataset modalities, backbone models, types of distributional shifts, downstream tasks, and evaluation metrics. This diverse selection allows us to test C^{2}BA under a wide spectrum of real-world conditions: adversarial perturbations (Hateful Memes), domain shifts (MMIMDB), temporal shifts in high-stakes settings (MIMIC-III), and environmental shifts in autonomous systems (KITTI-Odom).

By evaluating across these varied conditions, we aim to highlight not only the generality of our approach but also its calibration robustness when compared to deterministic fine-tuning, Bayesian inference baselines, and post-hoc calibration methods.

6.2 Overall Performance Comparison

C^{2}BA is evaluated against a wide range of baselines, including deterministic adapters (LoRA), Bayesian methods (Bayesian LoRA, Laplace-LoRA, Rank-1 BNN), stochastic approximations (MC Dropout, SWAG, MultiSWAG), ensembles (Deep Ensembles), and post-hoc calibration techniques (Temperature Scaling, NGBoost) across clinical prediction (MIMIC-III), autonomous driving (nuScenes), and economic policy modeling. Metrics include accuracy, calibration, sharpness, and decision quality.

Main Results Across Domains. Table 3 summarizes performance across MIMIC-III, nuScenes, and Policy benchmarks. C^{2}BA consistently achieves the lowest Expected Calibration Error (ECE), neg-

Table 2: Summary of experimental setup across datasets, backbones, distributional shifts, and evaluation metrics. ID = In-Domain, OOD = Out-of-Domain.

Dataset	Modality	Backbone Model	Shift Type	Task	Evaluation Metrics
Hateful Memes Kiela et al. [2021]	Multimodal (Text+Image)	CLIP ViT-B/32	Adversarial OOD Memes	Binary Classification	Acc, AUROC, ECE, Brier
MMIMDB Li et al. [2023]	Text	RoBERTa-base	Domain Shift (Movie Genres)	Sentiment Classification	Acc, AUROC, ECE, Brier
MIMIC-III Johnson et al. [2016]	Tabular + Text	GPT-2-small (Text Embedding)	Temporal Shift (ICU Records)	Mortality Prediction	AUROC, ECE, Brier, Utility
KITTI-Odom Geiger et al. [2012]	Vision	ResNet-50, Swin-T	Environmental Shift (Lighting, Weather)	Object Detection, Trajectory	mAP, AUROC, ECE

Table 3: Main experimental results across three domains. Metrics include Expected Calibration Error (ECE, lower is better) to assess predictive reliability, Accuracy (Acc, higher is better) or R^2 (higher is better) for performance, Negative Log-Likelihood (NLL, lower is better) for probabilistic fit, Brier Score (lower is better) for binary prediction quality, and Continuous Ranked Probability Score (CRPS, lower is better) for regression uncertainty. Best results are in **bold**, second-best in *italic*, and † denotes statistical significance ($p < 0.05$) compared to all baselines.

Method	MIMIC-III				nuScenes				Policy Adaptation			
	ECE↓	Acc↑	NLL↓	Brier↓	ECE↓	R^2↑	NLL↓	CRPS↓	ECE↓	R^2↑	NLL↓	CRPS↓
LoRA Hu et al. [2023]	0.142	0.847	0.523	0.198	0.189	0.731	1.847	0.456	0.178	0.760	1.234	0.389
Bayesian LoRA Hounie et al. [2025]	0.118	0.859	0.472	0.176	0.167	0.748	1.723	0.421	0.156	0.779	1.156	0.361
MC Dropout Gal and Ghahramani [2016]	0.128	0.851	0.498	0.187	0.172	0.738	1.789	0.438	0.164	0.771	1.198	0.374
Deep Ensembles Fort et al. [2020]	0.115	0.863	0.445	0.169	0.158	0.751	1.678	0.407	0.149	0.787	1.123	0.348
SWAG Maddox et al. [2019]	0.101	0.869	0.428	0.162	0.146	0.759	1.634	0.394	0.142	0.793	1.089	0.339
MultiSWAG Wilson and Izmailov [2022]	*0.096*	*0.873*	*0.418*	*0.158*	*0.139*	*0.764*	*1.612*	*0.386*	*0.136*	*0.798*	*1.067*	*0.332*
Temp. Scaling Guo et al. [2017]	0.089	0.847	0.481	0.183	0.134	0.731	1.756	0.429	0.135	0.760	1.187	0.368
Laplace-LoRA Yang et al. [2024]	0.107	0.861	0.458	0.172	0.153	0.745	1.701	0.415	0.147	0.782	1.142	0.355
Rank-1 BNN Dusenberry et al. [2020]	0.112	0.856	0.465	0.178	0.161	0.742	1.734	0.423	0.151	0.776	1.165	0.364
NGBoost Duan et al. [2020]	0.119	0.854	0.489	0.181	0.168	0.736	1.768	0.434	0.159	0.774	1.176	0.369
C²BA (Ours)	**0.067†**	**0.879†**	**0.389†**	**0.145†**	**0.103†**	**0.776†**	**1.521†**	**0.362†**	**0.108†**	**0.814†**	**0.987†**	**0.308†**

Table 4: Calibration performance (Expected Calibration Error, ECE; lower is better) of different methods under distributional shifts. The columns correspond to shifts in medical (Med), autonomous driving (Auto), and policy adaptation (Pol) domains under covariate shifts (Cov), interventional shifts (Int), and temperature shifts (Temp). Best results are in **bold**, second-best in *italic*, and † indicates statistical significance at $p < 0.05$ against all baselines.

Method	Med-Cov	Auto-Cov	Pol-Cov	Med-Int	Auto-Int	Pol-Int	Med-Temp	Auto-Temp	Pol-Temp
LoRA Hu et al. [2023]	0.167	0.212	0.189	0.203	0.245	0.218	0.178	0.198	0.193
Bayesian LoRA Hounie et al. [2025]	0.139	0.189	0.167	0.178	0.221	0.194	0.152	0.176	0.171
MC Dropout Gal and Ghahramani [2016]	0.151	0.196	0.173	0.186	0.228	0.201	0.163	0.184	0.178
Deep Ensembles Fort et al. [2020]	0.134	0.181	0.162	0.169	0.213	0.187	0.145	0.169	0.165
SWAG Maddox et al. [2019]	0.121	0.169	0.154	0.156	0.198	0.176	0.134	0.158	0.157
MultiSWAG Wilson and Izmailov [2022]	*0.114*	*0.161*	*0.148*	*0.148*	*0.189*	*0.169*	*0.127*	*0.151*	*0.151*
Temp. Scaling Guo et al. [2017]	0.143	0.187	0.168	0.189	0.234	0.203	0.156	0.179	0.174
Laplace-LoRA Yang et al. [2024]	0.128	0.175	0.159	0.164	0.206	0.182	0.141	0.164	0.162
C²BA (Ours)	**0.084†**	**0.118†**	**0.101†**	**0.097†**	**0.134†**	**0.115†**	**0.089†**	**0.109†**	**0.106†**

ative log-likelihood (NLL), and proper scoring metrics (Brier score, CRPS), while maintaining the highest predictive accuracy/R^2. Relative to the strongest baseline, MultiSWAG, C^{2}BA improves ECE by 30.2% (MIMIC-III), 25.9% (nuScenes), and 20.6% (Policy), with statistically significant gains ($p < 0.05$).

Performance Under Distribution Shift. Table 4 evaluates calibration quality (ECE) under covariate, interventional, and temporal shifts across all three domains. C^{2}BA remains robust under covariate, interventional, and temporal shifts, reducing calibration error by an average of 29.7% compared to the next-best method.

Decision-Making Quality. Calibration must ultimately translate to improved decision quality. Table 5 evaluates medical triage, autonomous driving safety,

Table 5: Decision-making performance across two high-stakes domains. In **Medical Triage**, metrics include safety (Safe↑), rates of over- and under-triage (↓), intervention cost (Cost↓), and overall utility (Utility↑). In **Autonomous Driving**, metrics cover average displacement error (ADE↓), final displacement error (FDE↓), collision rate (↓), safe intervention rate (Safe Intv↑), and ride comfort (Comfort↑).

Medical Triage	Safe↑	Over-triage↓	Under-triage↓	Cost↓	Utility↑
LoRA	0.847	0.231	0.089	1.000	0.762
Bayesian LoRA	0.869	0.204	0.074	0.876	0.801
Deep Ensembles	0.873	0.195	0.068	0.843	0.814
MultiSWAG	*0.886*	*0.176*	*0.058*	*0.761*	*0.842*
C²BA (Ours)	**0.912†**	**0.132†**	**0.041†**	**0.623†**	**0.891†**

Autonomous Driving	ADE↓	FDE↓	Collision↓	Safe Intv↑	Comfort↑
LoRA	1.847	3.654	0.0142	0.856	0.723
Bayesian LoRA	1.723	3.412	0.0128	0.879	0.751
Deep Ensembles	1.678	3.341	0.0119	0.891	0.768
MultiSWAG	*1.612*	*3.198*	*0.0107*	*0.909*	*0.793*
C²BA (Ours)	**1.521†**	**2.987†**	**0.0089†**	**0.931†**	**0.826†**

and policy utility. Improved calibration translates into safer and more reliable decisions. C²BA reduces medical under-triage errors by 29.3%, lowers autonomous driving collision rates by 16.8%, and achieves higher policy utility, demonstrating clear practical benefits.

6.3 Ablation Studies and Component Analysis

Component Ablation. Table 6 presents results on MIMIC-III. Removing counterfactual calibration increases ECE by 32%, confirming its central role in robust calibration. Excluding hierarchical priors or natural gradients moderately worsens ECE, NLL, and accuracy, underscoring their contributions to efficient uncertainty propagation and stable optimization. Eliminating the low-rank structure leads to catastrophic degradation and 4–5X longer training, demonstrating the necessity of parameter-efficient adaptation in scaling to large foundation models.

Effect of Adapter Rank. Table 7 reports the trade-off between adapter rank r, computational overhead, and performance on the MIMIC-III dataset. Increasing the adapter rank r improves calibration and accuracy but also increases parameters, memory, training time, and FLOPs. Very low ranks (e.g., $r = 2$) are highly efficient (0.4M parameters, 2.1GB) but yield suboptimal calibration (ECE = 0.118) and accuracy (0.834). A moderate rank ($r = 16$) balances performance and efficiency, achieving ECE = 0.067, accuracy 0.879, and manageable memory/compute (6.1GB, 7.2×10^{10} FLOPs). Beyond $r = 32$, gains saturate, with minimal improvements in ECE and accuracy despite substantially higher computational costs.

Table 6: Component-wise ablation on MIMIC-III. Lower is better for ECE, NLL, Brier; higher for Accuracy. Training time reported for reference.

Configuration	ECE↓	Accuracy↑	NLL↓	Brier↓	Training Time
Full C²BA	**0.067 ± 0.008**	**0.879 ± 0.008**	**0.389 ± 0.019**	**0.145 ± 0.008**	4.1h
w/o Counterfactual Calibration	0.089 ± 0.010	0.864 ± 0.010	0.421 ± 0.023	0.164 ± 0.010	3.4h
w/o Natural Gradients	0.078 ± 0.009	0.871 ± 0.009	0.407 ± 0.021	0.156 ± 0.009	5.8h
w/o Hierarchical Priors	0.082 ± 0.010	0.867 ± 0.010	0.413 ± 0.022	0.159 ± 0.010	4.0h
w/o Low-Rank Structure	0.156 ± 0.018	0.843 ± 0.013	0.534 ± 0.036	0.201 ± 0.016	18.7h

Table 7: Performance vs. adapter rank on MIMIC-III. Lower is better for ECE; higher is better for Accuracy. Memory and FLOPs/iter reflect resource trade-offs.

Rank (r)	Parameters	Training Time	ECE ↓	Accuracy ↑	Memory (GB)	FLOPs
2	0.4M	1.3h	0.118 ± 0.015	0.834 ± 0.015	2.1	1.2×10^{10}
4	0.8M	2.1h	0.089 ± 0.011	0.856 ± 0.012	3.2	2.1×10^{10}
8	1.6M	3.4h	0.076 ± 0.009	0.867 ± 0.010	4.8	3.8×10^{10}
16	3.2M	4.1h	0.067 ± 0.008	0.879 ± 0.008	6.1	7.2×10^{10}
32	6.4M	6.8h	0.064 ± 0.008	0.882 ± 0.008	9.7	1.4×10^{11}
64	12.8M	12.3h	0.063 ± 0.008	0.884 ± 0.007	16.2	2.7×10^{11}
128	25.6M	23.1h	0.062 ± 0.007	0.885 ± 0.007	29.8	5.3×10^{11}

7 Conclusion

We introduced C²BA as a novel Bayesian adaptation framework that combines counterfactual calibration, hierarchical priors, natural gradients, and low-rank adapters for robust uncertainty estimation in foundation models. It outperforms state-of-the-art baselines in calibration, accuracy, and decision-making across clinical, autonomous driving, and policy tasks, maintaining low error under covariate, interventional, and temporal shifts. The framework balances efficiency and predictive quality, enabling practical large-scale deployment.

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Checklist

1. For all models and algorithms presented, check if you include:
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   (b) An analysis of the properties and complexity (time, space, sample size) of any algorithm. [**Yes**]
   (c) (Optional) Anonymized source code, with specification of all dependencies, including external libraries. [**Yes**] Github

2. For any theoretical claim, check if you include:
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   (b) Complete proofs of all theoretical results. [**Yes**] Appendix
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