

Accelerated Sequential Posterior Inference via Reuse for Gravitational-Wave Analyses

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We introduce accelerated sequential posterior inference via reuse (ASPIRE), a broadly applicable framework that transforms existing posterior samples and Bayesian evidence estimates into unbiased results under alternative models without rerunning the original analysis. ASPIRE combines normalizing flows with a generalized sequential Monte Carlo (SMC) scheme, enabling efficient updates of existing results and reducing total likelihood evaluations and wall times by factors of up to 5.8 and 5.5, respectively, with larger gains per posterior sample. This addresses a growing problem in gravitational-wave astronomy, where events must be repeatedly reanalyzed under different models or physical hypotheses. We show that ASPIRE reproduces full Bayesian results when switching waveform models or adding physical effects such as spin precession and orbital eccentricity. With this statistical robustness, ASPIRE turns repeated reanalyses into fast, reliable updates—paving the way for systematic studies of waveform systematics, scalable reanalyses across large event catalogs, and broadly applicable Bayesian reanalysis across other scientific domains.

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Introduction—The LIGO-Virgo-KAGRA collaboration [1–3] has detected more than 200 gravitational-wave signals from compact binary mergers [4–8] and continues to regularly detect such signals [9]. These detections have shaped our understanding of the Universe on multiple scales [10] and enabled tests of general relativity [11]. As the catalog of events grows, a key challenge emerges: events must be reanalyzed repeatedly under different models or physical hypotheses. Understanding waveform systematics [12,13], adding effects such as orbital eccentricity [14,15], performing tests of general relativity [16], or modeling gravitational lensing [17] all require new analyses from scratch. This repeated reanalysis is rapidly becoming a computational bottleneck, limiting our ability to probe waveform systematics and to conduct comprehensive tests of fundamental physics.

Ideally, existing results would inform subsequent analyses. Naively using a previous posterior as the prior for a new analysis double counts data, which, if uncorrected, breaks model comparison via Bayes factors or posterior odds and leads to overly narrow posterior confidence intervals. Therefore, we require an algorithm that can incorporate existing samples while still producing unbiased posterior and Bayesian evidence estimates. Current

analyses typically use nested sampling [18,19], which estimates both the posterior and evidence but can take hours to days [20,21]. Many efforts have sought to directly accelerate inference [22–27], but these methods do not leverage existing results. The standard approach for reusing posteriors within gravitational-wave inference is importance sampling [28]; however, this fails when the initial and target distributions differ substantially. More sophisticated methods include Rapid inference via Iterative FITting (RIFT) [29] and posterior repartitioning [30], which can both be seeded from existing samples but require similar support to the posterior or fail when the distributions are disjoint [31]. Methods based on Markov chain Monte Carlo (MCMC) [32] and parallel tempered Markov chain Monte Carlo (PTMCMC) [33] have also been explored [34–38]. While PTMCMC can provide evidence estimates, gravitational-wave applications have not generally emphasized accurate evidence calculation, and robustness depends sensitively on choices such as the temperature ladder and mixing efficiency.

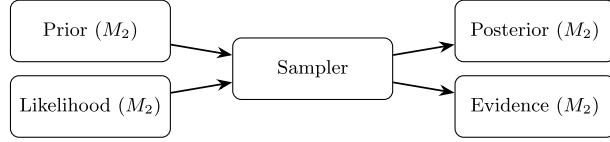
Here we present a novel framework: accelerated sequential posterior inference via reuse (ASPIRE). Instead of discarding existing results and repeating full analyses, posterior samples and the evidence estimate obtained under one model are updated to unbiased posterior samples and an evidence estimate under a new model. This approach remains valid even when the two posteriors occupy different regions of parameter space or when new parameters are introduced, enabling extensions to additional physical effects (e.g., orbital eccentricity [39]) and families of modified-gravity hypotheses [16]. ASPIRE, thus, enables repeated reanalyses via sequential reuse of existing results.

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Starting point: Posterior Samples (M_1), New Model (M_2)

Traditional inference



ASPIRE

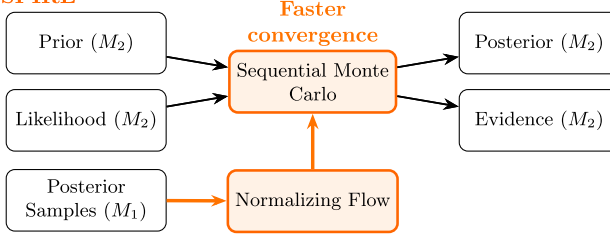


FIG. 1. Comparison of traditional Bayesian inference (top), which must perform full inference for a new model M_2 despite existing posterior samples with M_1 , with ASPIRE (bottom), which reuses the existing posterior samples under model M_1 via flow approximation and a sequential Monte Carlo update to obtain unbiased results under a new model M_2 .

ASPIRE combines normalizing flows with a generalized sequential Monte Carlo (SMC) scheme. We show that ASPIRE is robust and reproduces results that are statistically consistent with traditional analyses while reducing sampling time by up to 5.5 times. We demonstrate efficient updates between different waveform models and the recovery of new parameters such as for modeling spin precession [40] and orbital eccentricity [39], and we highlight an application to real data. By enabling analyses to be updated rather than repeated, ASPIRE provides a broadly applicable tool for gravitational-wave astronomy and other areas of physics where reanalyses are common.

Method—Bayesian inference traditionally proceeds by assuming a model M_1 that describes the data d and has parameters θ . It then combines a prior $p(\theta|M_1)$ with a likelihood $p(d|\theta, M_1)$ to obtain a posterior distribution $p(\theta|M_1, d)$. Each time the model or data changes, the full inference is typically repeated from scratch (Fig. 1, top), which becomes costly as data volumes and model complexities grow.

The ASPIRE framework introduces a new approach to sequentially updating existing results and requires two complementary steps. Instead of restarting from draws from the prior, ASPIRE begins with posterior samples obtained under an existing model M_1 (Fig. 1, bottom left). We approximate these samples using a normalizing flow [41], a flexible density estimator that maps a simple base distribution $q_z(z)$ into an approximation of the posterior $q_\phi(\theta)$ through an invertible transformation $f_\phi(\theta)$ described by parameters ϕ . Training the flow on the initial samples by maximum likelihood [41] yields

$$p(\theta|d, M_1) \approx q_\phi(\theta) = q_z(f_\phi(\theta)) \left| \frac{\partial f_\phi(\theta)}{\partial \theta} \right|. \quad (1)$$

This allows ASPIRE to start from an informed initial distribution rather than the prior. When M_2 has additional parameters, we extend the samples with draws from the prior and discard incompatible ones, ensuring that q_ϕ spans the parameter space of M_2 (see Supplemental Material [42]).

The second step (Fig. 1, bottom middle) is to evolve this distribution to the target posterior and to estimate the Bayesian evidence. We build on [60] and generalize SMC for this purpose. SMC for Bayesian inference evolves a set of samples through a sequence of intermediate distributions that interpolate between the prior and posterior via an inverse temperature β_i that anneals the likelihood [61]. In ASPIRE, the sequence instead interpolates between the flow-based approximation $q_\phi(\theta)$ and the true posterior under the new model M_2 :

$$p_i(\theta|d, M_2, \beta_i) \propto q_\phi(\theta)^{1-\beta_i} [p(d|\theta, M_2)p(\theta|M_2)]^{\beta_i}, \quad (2)$$

where $\beta_i \in [0, 1]$ controls the progression. The algorithm starts with samples from q_ϕ , and then at each iteration i the inverse temperature β_i is increased using an adaptive schedule. The samples are resampled according to $p_i(\theta|d, M_2, \beta_i)/p_{i-1}(\theta|d, M_2, \beta_{i-1})$ and then diversified using an MCMC step [62,63]. The algorithm terminates when $\beta_i = 1$, producing posterior samples and an evidence estimate. This approach guarantees unbiased results, even when the target and initial posteriors occupy different regions of the parameter space, since the annealing schedule ensures that successive intermediate distributions have sufficient overlap and the resampling and mutation steps allow particles to move between regions (see Fig. 4 of Supplemental Material [42] and the surrounding text).

Together, these two components, flow-based posterior approximation and generalized SMC evolution, define ASPIRE. This enables efficient reuse of existing results and allows analyses to be updated rather than repeated. The implementation details are provided in Supplemental Material [42], and we provide an open-source implementation in the Python package ASPIRE [64].

Results—We evaluate ASPIRE across simulated and real data, testing its robustness to waveform choice, added physical complexity, and detector calibration uncertainties.

We assess ASPIRE when changing the waveform model used to describe the signal, a key test to evaluate systematic uncertainties. We consider two waveform models that include spin precession and higher-order multipoles: IMRPhenomXPHM [65] and IMRPhenomXO4a [66], both used in GWTC-4.0 [8] to understand waveform systematics. Figure 2 compares results for two simulated signals analyzed with both waveforms, where ASPIRE updates an initial IMRPhenomXPHM run to obtain results with

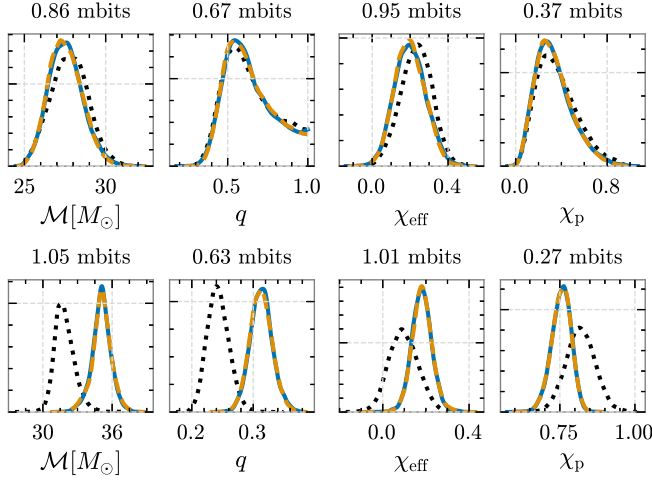


FIG. 2. Posterior distributions for two simulated binary black hole signals analyzed with different waveform models. Top: GW150914-like system with comparable masses and low spins. Bottom: highly spinning asymmetric system with $m_1/m_2 = 4$. Results are shown for IMRPhenomXPHM with Dynesty (black dotted line), IMRPhenomXO4a using ASPIRE, initialized from the IMRPhenomXPHM samples (orange dashed line), and IMRPhenomXO4a with Dynesty (blue solid line). Parameters shown are the chirp mass, mass ratio, effective aligned spin χ_{eff} , and effective precessing spin χ_p . The JSD in millibits (mbits) between the two IMRPhenomXO4a posteriors is quoted above each subplot.

IMRPhenomXO4a. We quantify the similarity between posterior distributions using the JSD (D_{JS}) in millibits (mbits), where larger values indicate greater differences, $D_{\text{JS}} \leq 50$ mbits denotes good agreement [4], and $D_{\text{JS}} \leq 2.1$ mbits indicates the distributions are statistically indistinguishable [21]. For both systems, the posteriors obtained with ASPIRE are in close agreement with the baseline, even for the asymmetric binary where the posterior shifts substantially.

We now consider analyses that incorporate additional physics, namely spin precession and orbital eccentricity. Starting with spin precession, we use ASPIRE to update a result obtained under the aligned spin assumption with IMRPhenomD [67,68], replacing it with the precessing model IMRPhenomPv2 [69,70]. This type of update is relevant in low-latency analyses, where simplifying assumptions are often made to reduce computational cost [71]. Figure 3 (top) compares the posterior distributions and finds that ASPIRE is consistent with a baseline analysis with $D_{\text{JS}} < 1.5$ mbits. This includes the precessing spin parameter χ_p , which captures physical effects absent from the initial aligned spin analysis.

Orbital eccentricity is astrophysically interesting because it provides a clear signature of dynamical formation channels [72], and several observed events show potential evidence for it [73–76]. However, incorporating eccentricity typically requires reanalyzing existing events, which can

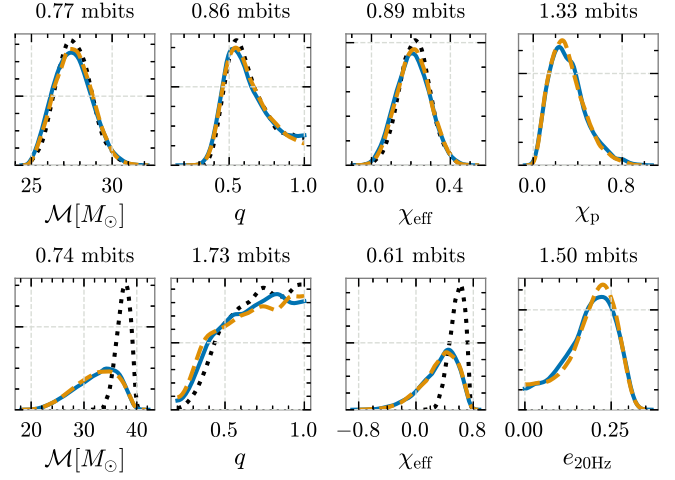


FIG. 3. Posterior distributions when adding new physical effects to an initial analysis. Top: spin-precessing analysis of a GW150914-like injection; results are shown for the IMRPhenomD (aligned spins) baseline with Dynesty (black dotted line), IMRPhenomPv2 (precessing spins) using ASPIRE initialized from the aligned spin samples (orange dashed line), and an IMRPhenomPv2 with Dynesty (blue solid line). Bottom: eccentric analysis of an aligned spin GW150914-like injection; results are shown for the TaylorF2 baseline with Dynesty (black dotted line), TaylorF2Ecc using ASPIRE initialized from the TaylorF2 result (orange dashed line), and TaylorF2Ecc with Dynesty (blue solid line). Parameters shown are the chirp mass, mass ratio, effective aligned spin χ_{eff} , and effective precessing spin χ_p (top) or eccentricity at 20 Hz $e_{20\text{Hz}}$ (bottom). The JSD in millibits (mbits) between the posteriors with the same waveform is quoted above each subplot.

be computationally expensive. To demonstrate robustness when adding this physics, we consider a simulated signal with $e_{20\text{Hz}} = 0.25$ and use ASPIRE to update a quasicircular aligned spin analysis with TaylorF2 [77] to the eccentric model TaylorF2Ecc [78]. Figure 3 (bottom) shows the posterior distributions, including the eccentricity posterior, which agrees with the baseline analysis.

These examples illustrate that ASPIRE incorporates new physical degrees of freedom without introducing bias, even in cases where the added parameters are strongly correlated with existing ones.

We apply ASPIRE to real data by reanalyzing GW150914 [79] and GW200129_065458 from GWTC-3 [7], an event known to exhibit waveform systematics [7,80–83]. We include calibration uncertainty [84] and follow a typical catalog workflow [85]: first analyzing each event with IMRPhenomXPHM, then IMRPhenomXO4a. GW150914 lies in a region of parameter space where these two waveform models are expected to agree broadly, whereas for GW200129 several parameters are known to be in tension between models. Figure 4 shows the posterior distributions for the masses and spins of both events. For GW150914, the posteriors differ only slightly between waveform models, consistent with previous reanalyses [86,87].

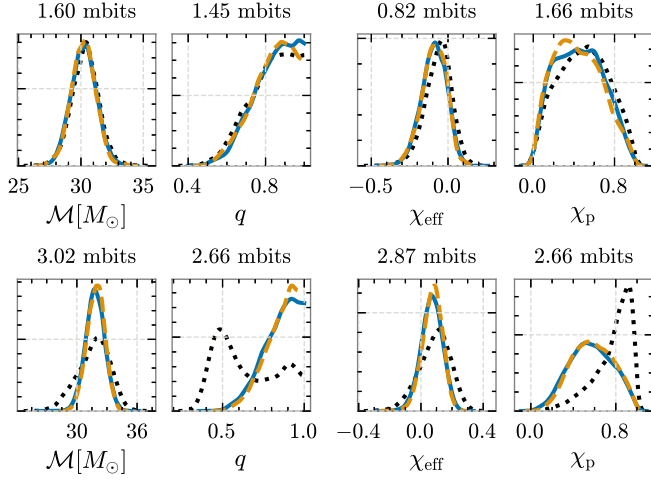


FIG. 4. Posterior distributions for real gravitational-wave events analyzed with ASPIRE. Top: the first detection, GW150914. Bottom: an event with known waveform systematics, GW200129. Parameters shown are the chirp mass and mass ratio and aligned spin χ_{eff} and effective precession spin χ_p . Results are shown for an initial analysis with IMRPhenomXPHM and Dynesty (black dotted line), an analysis with IMRPhenomXO4a and ASPIRE, updated from the initial analysis (orange dashed line), and a baseline analysis with IMRPhenomXO4a and Dynesty (blue solid line). The JSD in millibits (mbits) between the two IMRPhenomXO4a posteriors is quoted above each subplot.

The ASPIRE results are consistent with a baseline analysis, as supported by the JSD. For GW200129, as expected, we observe substantial waveform-driven differences. Nonetheless, ASPIRE remains consistent with the baseline analysis, though with more stringent settings (Supplemental Material [42]) and smaller efficiency gains (Table I). Overall, these results demonstrate that ASPIRE remains effective on real data provided the initial analysis is sufficiently informative.

To further demonstrate that ASPIRE produces statistically unbiased posterior distributions, we perform a probability-probability (P-P) test with 100 simulated binary black hole signals with spin precession and higher-order

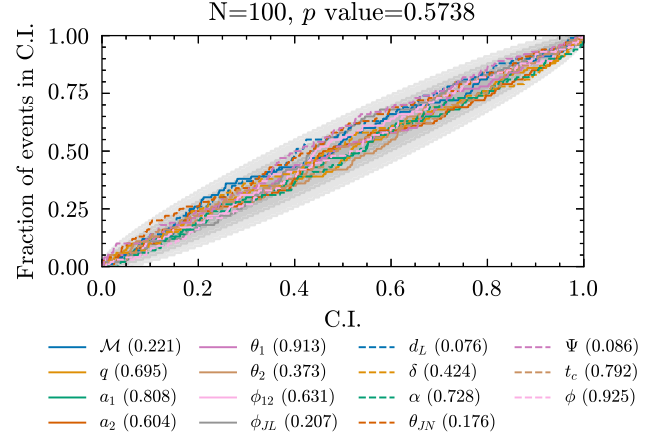


FIG. 5. Probability-probability (P-P) plot for 100 simulated binary black hole signals analyzed with ASPIRE. Signals were generated with IMRPhenomXPHM in a three-detector network and analyzed using Bilby with Dynesty. Initial samples were drawn from the prior to initialize ASPIRE. Shaded regions indicate 1-, 2-, and 3- σ confidence intervals. The combined p value of 0.574 demonstrates that the posteriors are statistically unbiased.

multipoles. We analyze these signals with ASPIRE and use initial samples from the prior. This produces the P-P plot shown in Fig. 5 with a combined p value of 0.574, confirming that the inferred posteriors are unbiased.

In addition to recovering unbiased posterior distributions, ASPIRE yields consistent evidence estimates. Table I presents the inferred log evidences for analyses using ASPIRE and Dynesty with the same waveform. The log-evidence differences between ASPIRE and Dynesty are within the estimated uncertainties, except for the asymmetric injection and GW200129, where they differ slightly. This agreement confirms that ASPIRE produces results consistent with baseline analyses and preserves statistical validity for Bayesian model comparison.

Table I presents the number of likelihood evaluations, wall times, and posterior sample counts for the analyses. For ASPIRE, we separately report the cost of the initial SMC evolution and the total cost including final posterior

TABLE I. Estimated log evidences (base e), likelihood evaluations, wall time, and number of posterior samples for analyses using ASPIRE and Dynesty. For ASPIRE, we separately report the initial SMC evolution cost and the total cost including posterior resampling.

Analysis	Log evidence		Likelihood evaluations [10^6]		Wall time [h]		Samples	
	Dynesty	ASPIRE	Dynesty	ASPIRE	Dynesty	ASPIRE	Dynesty	ASPIRE
Changing waveform (GW150914-like)	-57893.23 ± 0.16	-57893.36 ± 0.06	32.4	3.03/8.03	14.62	1.53/4.01	5810	10,000
Changing waveform ($q = 4$) ^a	-54802.73 ± 0.21	-54803.15 ± 0.07	49.6	25.6/40.6	15.68	10.29/16.02	6511	20,000
Adding spin precession	-57893.12 ± 0.15	-57893.11 ± 0.06	7.15	0.431/1.23	1.16	0.11/0.30	4737	10,000
Adding orbital eccentricity	-1928.15 ± 0.16	-1928.26 ± 0.06	27.1	4.55/7.55	0.66	0.19/0.30	4240	10,000
GW150914	-12767.84 ± 0.16	-12768.08 ± 0.07	32.2	4.54/9.54	11.59	1.05/2.09	5627	10,000
GW200129 ^a	-19556.51 ± 0.19	-19556.70 ± 0.03	53.6	37.7/52.7	19.45	11.24/13.93	7288	20,000

^aAnalyses marked use more stringent settings (see Supplemental Material [42]).

resampling. The initial SMC stage governs the adaptation of the existing posterior to the target distribution, while additional posterior samples can be generated at low cost (see Supplemental Material [42]). Across the scenarios considered here, ASPIRE reduces the cost of posterior adaptation by factors of up to 16.6 in likelihood evaluations and 11.1 in wall time. Including final posterior resampling, the total cost is reduced by up to 5.8 (12.3 per posterior sample), with corresponding wall time reductions of up to 5.5 (9.8 per posterior sample). More challenging updates, such as the asymmetric injection and GW200129, require more conservative settings and, therefore, yield smaller gains.

Discussion and outlook—ASPIRE establishes a novel approach for Bayesian inference in gravitational-wave astronomy. Rather than discarding results and restarting analyses from the prior, posterior results can be transformed into unbiased results under new models, including new posterior samples and an evidence estimate, that are consistent with traditional analyses. By demonstrating that sequential inference via reuse of existing results is both practical and statistically robust, ASPIRE provides a new tool for systematic exploration of waveform systematics and physical hypotheses.

Our studies highlight the immediate utility of this approach. ASPIRE reproduces full Bayesian results across waveform approximants, recovers additional physical effects such as spin precession and orbital eccentricity, and passes stringent statistical validation tests. In all cases, the method yields posteriors and evidence estimates consistent with baseline inferences while reducing the computational cost of repeated reanalyses, with reductions in total likelihood evaluations and wall times of up to 5.8 and 5.5, respectively. When normalized by the number of posterior samples produced, the efficiency gains are even larger. These gains transform tasks that were previously prohibitive, such as repeated waveform comparisons or large-scale catalog updates, into routine analyses. In doing so, ASPIRE maximizes the scientific return from the rapidly growing catalog of gravitational-wave detections [8]. However, the efficiency of ASPIRE depends on the similarity between the initial and target posteriors. As this discrepancy increases, more SMC steps are required, reducing the computational advantage; in practice, known differences can often be mitigated by augmenting the initial samples with prior draws (Supplemental Material [42]). Predicting performance *a priori* remains an open problem.

Several approaches have been proposed to accelerate or reuse existing inference results, including importance sampling [28], nested-sampling initialization strategies [30,31], and tempered MCMC methods [33,35–38,88,89]. Among these, PTMCMC is the most directly comparable to ASPIRE. By evolving chains across a temperature ladder, PTMCMC can explore multimodal structure and access regions not present in an initialization; however, its

performance depends sensitively on temperature ladder design and mixing. In contrast, ASPIRE automatically constructs a sequence of intermediate distributions between a learned approximation and the target posterior, enabling targeted updates of existing results. From the comparisons in Supplemental Material [42], ASPIRE provides more efficient inference and more stable evidence estimates in the scenarios considered, while exhibiting limitations associated with its reliance on the support of the initial distribution. These approaches, therefore, target different inference regimes.

Looking forward, the framework offers clear paths for further improvement. Future improvements, including gradient-based proposals [90] and particle recycling [91,92], could further accelerate ASPIRE. Since SMC is naturally parallelizable, the framework is well suited to GPU and low-latency applications. Furthermore, alternative schemes for tempering and sequential updates could be explored [89,93,94]. These developments position ASPIRE to benefit directly from advances in both algorithms and computing hardware.

Beyond methodological advances, ASPIRE has a wide range of potential applications. In gravitational-wave astronomy, it can support systematic waveform model comparisons, large-scale tests of general relativity, rapid reanalyses of candidate events, and efficient updates of entire catalogs as models improve. It could be used to refine approximate posterior estimates from low-latency approaches [26,27,95]. Early warning and low-latency pipelines [71,96] could incorporate ASPIRE to refine source characterization in real time. The framework also extends naturally to other fields where competing models abound, such as reinterpreting particle physics measurements under alternative theoretical models [97] or reanalyzing cosmological data when performing Bayesian model comparison [98,99]. By enabling fast and unbiased reanalyses, ASPIRE opens the way to scalable and systematic Bayesian inference across diverse scientific domains.

The ASPIRE [64], ASPIRE-BILBY [100], and ASPIRE-GW [101] software packages are available via PyPI [102–104] and the source code at [105–107]. This work used the following software packages: ARRAY-API-COMPAT [108], Bilby [109,110], BILBY_pipe [21], CORNER [111], Dynesty [112], GWFLOW [113], LALSuite [114,115], Matplotlib [116], MINIPCN [117], NumPy [118], PESummary [119], PTMCEE [88,120], PyTorch [121], SciPy [122,123], SEABORN [124], and ZUKO [125].

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Data availability—The results presented in this letter and code to reproduce the analyses are available at [127,128].

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- [1] J. Aasi *et al.* (LIGO Scientific Collaboration), Advanced LIGO, *Classical Quantum Gravity* **32**, 074001 (2015).
 - [2] F. Acernese *et al.* (VIRGO Collaboration), Advanced Virgo: A second-generation interferometric gravitational wave detector, *Classical Quantum Gravity* **32**, 024001 (2015).
 - [3] T. Akutsu *et al.* (KAGRA Collaboration), Overview of KAGRA: Detector design and construction history, *Prog. Theor. Exp. Phys.* **2021**, 05A101 (2021).
 - [4] B. P. Abbott *et al.* (LIGO Scientific and Virgo Collaborations), GWTC-1: A gravitational-wave transient catalog of compact binary mergers observed by LIGO and Virgo during the first and second observing runs, *Phys. Rev. X* **9**, 031040 (2019).
 - [5] R. Abbott *et al.* (LIGO Scientific and Virgo Collaborations), GWTC-2: Compact binary coalescences observed by LIGO and Virgo during the first half of the third observing run, *Phys. Rev. X* **11**, 021053 (2021).
 - [6] R. Abbott *et al.* (LIGO Scientific and VIRGO Collaborations), GWTC-2.1: Deep extended catalog of compact binary coalescences observed by LIGO and Virgo during the first half of the third observing run, *Phys. Rev. D* **109**, 022001 (2024).
 - [7] R. Abbott *et al.* (KAGRA, VIRGO, and LIGO Scientific Collaborations), GWTC-3: Compact clby LIGO and Virgo during the second part of the third observing run, *Phys. Rev. X* **13**, 041039 (2023).
 - [8] GWTC-4.0: Updating the gravitational-wave transient catalog with observations from the first part of the fourth LIGO-Virgo-KAGRA observing run, [arXiv:2508.18082](https://arxiv.org/abs/2508.18082).
 - [9] LIGO Scientific Collaboration, LIGO-G2302098: LIGO-Virgo-KAGRA cumulative detection plot—O1-O4b, <https://dcc.ligo.org/LIGO-G2302098-v15/public> (2025), accessed: July 7, 2025.
 - [10] R. Abbott *et al.* (LIGO Scientific, Virgo, and KAGRA Collaborations), Constraints on the cosmic expansion history from GWTC-3, *Astrophys. J.* **949**, 76 (2023).
 - [11] GWTC-4.0: Constraints on the cosmic expansion rate and modified gravitational-wave propagation, [arXiv:2509.04348](https://arxiv.org/abs/2509.04348).
 - [12] R. Gamba, M. Breschi, S. Bernuzzi, M. Agathos, and A. Nagar, Waveform systematics in the gravitational-wave inference of tidal parameters and equation of state from binary neutron star signals, *Phys. Rev. D* **103**, 124015 (2021).
 - [13] A. B. Yelikar, R. O. Shaughnessy, J. Lange, and A. Z. Jan, Waveform systematics in gravitational-wave inference of signals from binary neutron star merger models incorporating higher-order modes information, *Phys. Rev. D* **110**, 064024 (2024).
 - [14] A. Gamboa *et al.*, Accurate waveforms for eccentric, aligned-spin binary black holes: The multipolar effective-one-body model SEOBNRv5EHM, *Phys. Rev. D* **112**, 044038 (2025).
 - [15] A. Nagar, R. Gamba, P. Rettegno, V. Fantini, and S. Bernuzzi, Effective-one-body waveform model for non-circularized, planar, coalescing black hole binaries: The importance of radiation reaction, *Phys. Rev. D* **110**, 084001 (2024).
 - [16] N. V. Krishnendu and F. Ohme, Testing general relativity with gravitational waves: An overview, *Universe* **7**, 497 (2021).
 - [17] R. Abbott *et al.* (LIGO Scientific and VIRGO Collaborations), Search for lensing signatures in the gravitational-wave observations from the first half of LIGO-Virgo's third observing run, *Astrophys. J.* **923**, 14 (2021).
 - [18] J. Skilling, Nested sampling, *AIP Conf. Proc.* **735**, 395 (2004).
 - [19] J. Skilling, Nested sampling for general Bayesian computation, *Bayesian Anal.* **1**, 833 (2006).
 - [20] J. Veitch *et al.*, Parameter estimation for compact binaries with ground-based gravitational-wave observations using the LALInference software library, *Phys. Rev. D* **91**, 042003 (2015).
 - [21] I. M. Romero-Shaw *et al.*, Bayesian inference for compact binary coalescences with Bilby: Validation and application to the first LIGO-Virgo gravitational-wave transient catalogue, *Mon. Not. R. Astron. Soc.* **499**, 3295 (2020).
 - [22] M. J. Williams, J. Veitch, and C. Messenger, Nested sampling with normalizing flows for gravitational-wave inference, *Phys. Rev. D* **103**, 103006 (2021).
 - [23] M. J. Williams, J. Veitch, and C. Messenger, Importance nested sampling with normalising flows, *Mach. Learn. Sci. Tech.* **4**, 035011 (2023).
 - [24] A. J. K. Chua and M. Vallisneri, Learning Bayesian posteriors with neural networks for gravitational-wave inference, *Phys. Rev. Lett.* **124**, 041102 (2020).
 - [25] H. Gabbard, C. Messenger, I. S. Heng, F. Tonolini, and R. Murray-Smith, Bayesian parameter estimation using conditional variational autoencoders for gravitational-wave astronomy, *Nat. Phys.* **18**, 112 (2022).
 - [26] M. Dax, S. R. Green, J. Gair, M. Pürrer, J. Wildberger, J. H. Macke, A. Buonanno, and B. Schölkopf, Neural importance sampling for rapid and reliable gravitational-wave inference, *Phys. Rev. Lett.* **130**, 171403 (2023).

- [27] S. Fairhurst, C. Hoy, R. Green, C. Mills, and S. A. Usman, Simple parameter estimation using observable features of gravitational-wave signals, *Phys. Rev. D* **108**, 082006 (2023).
- [28] G. Ashton, Reconstructing and resampling: A guide to utilising posterior samples from gravitational wave observations, *RAS Tech. Instrum.* **5**, rzag012 (2026).
- [29] J. Lange, R. O’Shaughnessy, and M. Rizzo, Rapid and accurate parameter inference for coalescing, precessing compact binaries, [arXiv:1805.10457](https://arxiv.org/abs/1805.10457).
- [30] M. Prathaban, H. Bevens, and W. Handley, Accelerated nested sampling with β -flows for gravitational waves, *Mon. Not. R. Astron. Soc.* **541**, 200 (2025).
- [31] M. Prathaban, C. Hoy, and M. J. Williams, Leveraging rapid parameter estimates for efficient gravitational-wave Bayesian inference via posterior repartitioning, [arXiv:2601.21630](https://arxiv.org/abs/2601.21630).
- [32] D. W. Hogg and D. Foreman-Mackey, Data analysis recipes: Using Markov Chain Monte Carlo, *Astrophys. J. Suppl. Ser.* **236**, 11 (2018).
- [33] D. J. Earl and M. W. Deem, Parallel tempering: Theory, applications, and new perspectives, *Phys. Chem. Chem. Phys. (Incorporating Faraday Transactions)* **7**, 3910 (2005).
- [34] G. Ashton and C. Talbot, Bilby-MCMC: An MCMC sampler for gravitational-wave inference, *Mon. Not. R. Astron. Soc.* **507**, 2037 (2021).
- [35] N. E. Wolfe, C. Talbot, and J. Golomb, Accelerating tests of general relativity with gravitational-wave signals using hybrid sampling, *Phys. Rev. D* **107**, 104056 (2023).
- [36] M. Falxa, S. Babak, and M. Le Jeune, Adaptive kernel density estimation proposal in gravitational wave data analysis, *Phys. Rev. D* **107**, 022008 (2023).
- [37] T. B. Littenberg and N. J. Cornish, Prototype global analysis of LISA data with multiple source types, *Phys. Rev. D* **107**, 063004 (2023).
- [38] N. Korsakova, S. Babak, M. L. Katz, N. Karnesis, S. Khukhlaev, and J. R. Gair, Neural density estimation for Galactic binaries in the LISA data analysis, *Phys. Rev. D* **110**, 104069 (2024).
- [39] P. C. Peters and J. Mathews, Gravitational radiation from point masses in a Keplerian orbit, *Phys. Rev.* **131**, 435 (1963).
- [40] T. A. Apostolatos, C. Cutler, G. J. Sussman, and K. S. Thorne, Spin induced orbital precession and its modulation of the gravitational wave forms from merging binaries, *Phys. Rev. D* **49**, 6274 (1994).
- [41] G. Papamakarios, E. Nalisnick, D. J. Rezende, S. Mohamed, and B. Lakshminarayanan, Normalizing flows for probabilistic modeling and inference, *J. Mach. Learn. Res.* **22**, 2617 (2021), <http://jmlr.org/papers/v22/19-1028.html>.
- [42] See Supplemental Material at <http://link.aps.org/supplemental/10.1103/PhysRevD.107.022008> for additional implementation and analysis details, which includes Refs. [43–59].
- [43] M. Karamanis, D. Nabergoj, F. Beutler, J. A. Peacock, and U. Seljak, pocoMC: A Python package for accelerated Bayesian inference in astronomy and cosmology, *J. Open Source Software* **7**, 4634 (2022).
- [44] A. W. v. d. Vaart, Delta method, in *Asymptotic Statistics*, Cambridge Series in Statistical and Probabilistic Mathematics (Cambridge University Press, Cambridge, England, 1998), pp. 25–34.
- [45] R. Douc and O. Cappé, Comparison of resampling schemes for particle filtering, in *ISPA 2005. Proceedings of the 4th International Symposium on Image and Signal Processing and Analysis, 2005* (IEEE, New York, 2005), pp. 64–69.
- [46] R. D. P. Grumitt, M. Karamanis, and U. Seljak, Sequential Kalman tuning of the t-preconditioned Crank-Nicolson algorithm: Efficient adaptive and gradient-free inference for Bayesian inverse problems, *Inverse Probl.* **40**, 125023 (2024).
- [47] N. Bose and A. Pai, Effective chirp mass in the inspiral frequency evolution of the nonspinning eccentric compact binary, *Phys. Rev. D* **104**, 124021 (2021).
- [48] G. Papamakarios, T. Pavlakou, and I. Murray, Masked autoregressive flow for density estimation, [arXiv:1705.07057](https://arxiv.org/abs/1705.07057).
- [49] D. Ward, Flowjax: Distributions and normalizing flows in jax, [10.5281/zenodo.10402073](https://doi.org/10.5281/zenodo.10402073) (2025).
- [50] D. P. Kingma and J. Ba, Adam: A method for stochastic optimization, [arXiv:1412.6980](https://arxiv.org/abs/1412.6980).
- [51] I. Loshchilov and F. Hutter, SGDR: Stochastic gradient descent with warm restarts, [arXiv:1608.03983](https://arxiv.org/abs/1608.03983).
- [52] B. P. Abbott *et al.* (KAGRA, LIGO Scientific, and Virgo Collaborations), Prospects for observing and localizing gravitational-wave transients with Advanced LIGO, Advanced Virgo and KAGRA, *Living Rev. Relativity* **19**, 1 (2016).
- [53] E. Baird, S. Fairhurst, M. Hannam, and P. Murphy, Degeneracy between mass and spin in black-hole-binary waveforms, *Phys. Rev. D* **87**, 024035 (2013).
- [54] E. Thrane and C. Talbot, An introduction to Bayesian inference in gravitational-wave astronomy: Parameter estimation, model selection, and hierarchical models, *Pub. Astron. Soc. Aust.* **36**, e010 (2019); *Pub. Astron. Soc. Aust.* **37**, e036(E) (2020).
- [55] S. Kullback and R. A. Leibler, On information and sufficiency, *Ann. Math. Stat.* **22**, 79 (1951).
- [56] E. Hellinger, Neue begründung der theorie quadratischer formen von unendlichvielen veränderlichen, *J. Reine Angew. Math.* **136**, 210 (1909).
- [57] J. Annis, N. J. Evans, B. J. Miller, and T. J. Palmeri, Thermodynamic integration and steppingstone sampling methods for estimating bayes factors: A tutorial, *J. Math. Psychol.* **89**, 67 (2019).
- [58] A. Gelman and D. B. Rubin, Inference from iterative simulation using multiple sequences, *Stat. Sci.* **7**, 457 (1992).
- [59] M. J. Williams, J. Veitch, and C. Chapman-Bird, mj-will/nessai: v0.15.2, [10.5281/zenodo.18711786](https://doi.org/10.5281/zenodo.18711786) (2026).
- [60] M. J. Williams, M. Karamanis, Y. Luo, and U. Seljak, Validating sequential Monte Carlo for gravitational-wave inference, *Mon. Not. R. Astron. Soc.* **543**, 1479 (2025).
- [61] J. M. Bernardo, M. J. Bayarri, J. O. Berger, A. P. Dawid, D. Heckerman, A. F. M. Smith, M. West, J. M. Bernardo, M. J. Bayarri *et al.*, *Sequential Monte Carlo for Bayesian Computation* (Oxford University Press, Oxford, UK, 2007), [10.1093/oso/9780199214655.003.0005](https://doi.org/10.1093/oso/9780199214655.003.0005).

- [62] P. Del Moral, A. Doucet, and A. Jasra, An adaptive sequential Monte Carlo method for approximate Bayesian computation, *Stat. Comput.* **22**, 1009 (2012).
- [63] P. Fearnhead and B. M. Taylor, An adaptive sequential Monte Carlo sampler, *Bayesian Anal.* **8**, 411 (2013).
- [64] M. J. Williams, A. Garron, F. Santoliquido, J. Tissino, and K. Leyde, *mj-will/ASPIRE: v0.1.0a19*, [10.5281/zenodo.19224148](https://doi.org/10.5281/zenodo.19224148) (2026).
- [65] G. Pratten *et al.*, Computationally efficient models for the dominant and subdominant harmonic modes of precessing binary black holes, *Phys. Rev. D* **103**, 104056 (2021).
- [66] J. E. Thompson, E. Hamilton, L. London, S. Ghosh, P. Kolitsidou, C. Hoy, and M. Hannam, PhenomXO4a: A phenomenological gravitational-wave model for precessing black-hole binaries with higher multipoles and asymmetries, *Phys. Rev. D* **109**, 063012 (2024).
- [67] S. Husa, S. Khan, M. Hannam, M. Pürrer, F. Ohme, X. Jiménez Forteza, and A. Bohé, Frequency-domain gravitational waves from nonprecessing black-hole binaries. I. New numerical waveforms and anatomy of the signal, *Phys. Rev. D* **93**, 044006 (2016).
- [68] S. Khan, S. Husa, M. Hannam, F. Ohme, M. Pürrer, X. Jiménez Forteza, and A. Bohé, Frequency-domain gravitational waves from nonprecessing black-hole binaries. II. A phenomenological model for the advanced detector era, *Phys. Rev. D* **93**, 044007 (2016).
- [69] P. Schmidt, M. Hannam, and S. Husa, Towards models of gravitational waveforms from generic binaries: A simple approximate mapping between precessing and nonprecessing inspiral signals, *Phys. Rev. D* **86**, 104063 (2012).
- [70] M. Hannam, P. Schmidt, A. Bohé, L. Haegel, S. Husa, F. Ohme, G. Pratten, and M. Pürrer, Simple model of complete precessing black-hole-binary gravitational waveforms, *Phys. Rev. Lett.* **113**, 151101 (2014).
- [71] S. Morisaki, R. Smith, L. Tsukada, S. Sachdev, S. Stevenson, C. Talbot, and A. Zimmerman, Rapid localization and inference on compact binary coalescences with the Advanced LIGO-Virgo-KAGRA gravitational-wave detector network, *Phys. Rev. D* **108**, 123040 (2023).
- [72] I. Mandel and F. S. Broekgaarden, Rates of compact object coalescences, *Living Rev. Relativity* **25**, 1 (2022).
- [73] I. M. Romero-Shaw, P. D. Lasky, E. Thrane, and J. C. Bustillo, GW190521: Orbital eccentricity and signatures of dynamical formation in a binary black hole merger signal, *Astrophys. J. Lett.* **903**, L5 (2020).
- [74] I. M. Romero-Shaw, P. D. Lasky, and E. Thrane, Four eccentric mergers increase the evidence that LIGO–Virgo–KAGRA’s binary black holes form dynamically, *Astrophys. J.* **940**, 171 (2022).
- [75] N. Gupte *et al.*, Evidence for eccentricity in the population of binary black holes observed by LIGO-Virgo-KAGRA, *Phys. Rev. D* **112**, 104045 (2025).
- [76] G. Morras, G. Pratten, and P. Schmidt, Orbital eccentricity in a neutron star—black hole binary, *Astrophys. J. Lett.* **1000**, L2 (2026).
- [77] A. Buonanno, B. Iyer, E. Ochsner, Y. Pan, and B. S. Sathyaprakash, Comparison of post-Newtonian templates for compact binary inspiral signals in gravitational-wave detectors, *Phys. Rev. D* **80**, 084043 (2009).
- [78] B. Moore, M. Favata, K. G. Arun, and C. K. Mishra, Gravitational-wave phasing for low-eccentricity inspiraling compact binaries to 3PN order, *Phys. Rev. D* **93**, 124061 (2016).
- [79] B. P. Abbott *et al.* (LIGO Scientific and Virgo Collaborations), GW150914: First results from the search for binary black hole coalescence with Advanced LIGO, *Phys. Rev. D* **93**, 122003 (2016).
- [80] A. H. Nitz, S. Kumar, Y.-F. Wang, S. Kastha, S. Wu, M. Schäfer, R. Dhurkunde, and C. D. Capano, 4-OGC: Catalog of gravitational waves from compact binary mergers, *Astrophys. J.* **946**, 59 (2023).
- [81] M. Hannam *et al.*, General-relativistic precession in a black-hole binary, *Nature (London)* **610**, 652 (2022).
- [82] E. Payne, S. Hourihane, J. Golomb, R. Udall, R. Udall, D. Davis, and K. Chatziioannou, Curious case of GW200129: Interplay between spin-precession inference and data-quality issues, *Phys. Rev. D* **106**, 104017 (2022).
- [83] R. Macas, A. Lundgren, and G. Ashton, Revisiting the evidence for precession in GW200129 with machine learning noise mitigation, *Phys. Rev. D* **109**, 062006 (2024).
- [84] A. Viets *et al.*, Reconstructing the calibrated strain signal in the Advanced LIGO detectors, *Classical Quantum Gravity* **35**, 095015 (2018).
- [85] A. G. Abac *et al.* (LIGO Scientific, VIRGO, and KAGRA Collaborations), GWTC-4.0: Methods for identifying and characterizing gravitational-wave transients, [arXiv:2508.18081](https://arxiv.org/abs/2508.18081).
- [86] G. Pratten, S. Husa, C. Garcia-Quiros, M. Colleoni, A. Ramos-Buades, H. Estelles, and R. Jaume, Setting the cornerstone for a family of models for gravitational waves from compact binaries: The dominant harmonic for nonprecessing quasicircular black holes, *Phys. Rev. D* **102**, 064001 (2020).
- [87] L. Pompili *et al.*, Laying the foundation of the effective-one-body waveform models SEOBNRv5: Improved accuracy and efficiency for spinning nonprecessing binary black holes, *Phys. Rev. D* **108**, 124035 (2023).
- [88] W. D. Voudsen, W. M. Farr, and I. Mandel, Dynamic temperature selection for parallel tempering in Markov chain Monte Carlo simulations, *Mon. Not. R. Astron. Soc.* **455**, 1919 (2016).
- [89] M. M. Graham and A. J. Storkey, Continuously tempered Hamiltonian Monte Carlo, [arXiv:1704.03338](https://arxiv.org/abs/1704.03338).
- [90] A. Buchholz, N. Chopin, and P. E. Jacob, Adaptive tuning of Hamiltonian Monte Carlo within sequential Monte Carlo, *Bayesian Anal.* **16**, 745 (2021).
- [91] T. Le Thu Nguyen, F. Septier, G. W. Peters, and Y. Delignon, Improving SMC sampler estimate by recycling all past simulated particles, in *2014 IEEE Workshop on Statistical Signal Processing (SSP)* (Institute of Electrical and Electronics Engineers, Gold Coast, Australia, 2014), pp. 117–120, [10.1109/SSP.2014.6884589](https://doi.org/10.1109/SSP.2014.6884589).
- [92] M. Karamanis and U. Seljak, Persistent sampling: Enhancing the efficiency of sequential Monte Carlo, *Stat. Comput.* **35**, 1 (2025).
- [93] R. M. Neal, Annealed importance sampling, [arXiv:physics/9803008](https://arxiv.org/abs/physics/9803008).

- [94] S. Syed, A. Bouchard-Côté, K. Chern, and A. Doucet, Optimised annealed sequential Monte Carlo samplers, [arXiv:2408.12057](https://arxiv.org/abs/2408.12057).
- [95] A. H. Nitz, Robust, rapid, and simple gravitational-wave parameter estimation, *Phys. Rev. D* **112**, 023032 (2025).
- [96] G. Cabourn Davies *et al.*, Premerger observation and characterization of massive black hole binaries, *Phys. Rev. D* **111**, 043045 (2025).
- [97] L. Gärtner, N. Hartmann, L. Heinrich, M. Horstmann, T. Kuhr, M. Reboud, S. Stefkova, and D. van Dyk, Constructing model-agnostic likelihoods, a method for the reinterpretation of particle physics results, *Eur. Phys. J. C* **84**, 693 (2024).
- [98] R. Arjona, L. Espinosa-Portales, J. García-Bellido, and S. Nesseris, A GREAT model comparison against the cosmological constant, *Phys. Dark Universe* **36**, 101029 (2022).
- [99] Z. G. Lane, A. Seifert, R. Ridden-Harper, and D. L. Wiltshire, Cosmological foundations revisited with Pantheon+, *Mon. Not. R. Astron. Soc.* **536**, 1752 (2025).
- [100] M. J. Williams, mj-will/ASPIRE-Bilby: v0.1.0a2, [10.5281/zenodo.17540602](https://zenodo.org/record/17540602) (2025).
- [101] M. J. Williams, mj-will/ASPIRE-GW: v0.1.0a1, [10.5281/zenodo.17183944](https://zenodo.org/record/17183944) (2025).
- [102] M. J. Williams, ASPIRE-INFERENCE, Python Package Index (PyPI) (2025), <https://pypi.org/project/aspire-inference/>.
- [103] M. J. Williams, ASPIRE-BILBY, Python Package Index (PyPI) (2025), <https://pypi.org/project/aspire-bilby/>.
- [104] M. J. Williams, ASPIRE-GW, Python Package Index (PyPI) (2025), <https://pypi.org/project/aspire-gw/>.
- [105] <https://github.com/mj-will/aspire>.
- [106] <https://github.com/mj-will/aspire-bilby>.
- [107] <https://github.com/mj-will/aspire-gw>.
- [108] Consortium for Python Data API Standards, ARRAY-API-COMPAT, <https://pypi.org/project/array-api-compat/> (2025).
- [109] G. Ashton *et al.*, Bilby: A user-friendly Bayesian inference library for gravitational-wave astronomy, *Astrophys. J. Suppl. Ser.* **241**, 27 (2019).
- [110] C. Talbot *et al.*, Bilby-dev/bilby: v2.5.2, [10.5281/zenodo.15586392](https://zenodo.org/record/15586392) (2025).
- [111] D. Foreman-Mackey, CORNER.PY: Scatterplot matrices in Python, *J. Open Source Software* **1**, 24 (2016).
- [112] J. S. Speagle, DYNESTY: A dynamic nested sampling package for estimating Bayesian posteriors and evidences, *Mon. Not. R. Astron. Soc.* **493**, 3132 (2020).
- [113] M. J. Williams, mj-will/GWFLOW: v0.1.0a1, [10.5281/zenodo.17182521](https://zenodo.org/record/17182521) (2025).
- [114] LIGO Scientific Collaboration, LIGO Algorithm Library—LALSuite, free software (GPL), [10.7935/GT1W-FZ16](https://zenodo.org/record/107935) (2018).
- [115] K. Wette, SWIGLAL: Python and OCTAVE interfaces to the LALSuite gravitational-wave data analysis libraries, *SoftwareX* **12**, 100634 (2020).
- [116] J. D. Hunter, Matplotlib: A 2d graphics environment, *Comput. Sci. Eng.* **9**, 90 (2007).
- [117] M. J. Williams, mj-will/MINIPCN, [10.5281/zenodo.15657998](https://zenodo.org/record/15657998) (2025).
- [118] C. R. Harris *et al.*, Array programming with NumPy, *Nature (London)* **585**, 357 (2020).
- [119] C. Hoy and V. Raymond, PESummary: The code agnostic parameter estimation summary page builder, *SoftwareX* **15**, 100765 (2021).
- [120] D. Foreman-Mackey, D. W. Hogg, D. Lang, and J. Goodman, EMCEE: The MCMC Hammer, *Publ. Astron. Soc. Pac.* **125**, 306 (2013).
- [121] A. Paszke *et al.*, PyTorch: An imperative style, high-performance deep learning library, [arXiv:1912.01703](https://arxiv.org/abs/1912.01703).
- [122] Wes McKinney, Data structures for statistical computing in Python, in *Proceedings of the 9th Python in Science Conference*, edited by Stéfan van der Walt and Jarrod Millman (SciPy Conference, Austin, Texas, USA, 2010), pp. 56—61, [10.25080/Majora-92bf1922-00a](https://zenodo.org/record/1025080).
- [123] P. Virtanen *et al.* (SciPy 1.0 Contributors), SciPy 1.0: Fundamental algorithms for scientific computing in Python, *Nat. Methods* **17**, 261 (2020).
- [124] M. L. Waskom, SEABORN: Statistical data visualization, *J. Open Source Software* **6**, 3021 (2021).
- [125] F. Rozet *et al.*, ZUKO: Normalizing flows in PyTorch, [10.5281/zenodo.7625672](https://zenodo.org/record/7625672) (2024).
- [126] R. Abbott *et al.* (LIGO Scientific and Virgo Collaborations), Open data from the first and second observing runs of Advanced LIGO and Advanced Virgo, *SoftwareX* **13**, 100658 (2021).
- [127] M. J. Williams, Accelerated Sequential Posterior Inference via Reuse for Gravitational-Wave Analyses—Data Release, [10.5281/zenodo.17514969](https://zenodo.org/record/17514969) (2025).
- [128] M. J. Williams, Accelerated Sequential Posterior Inference via Reuse for Gravitational-Wave Analyses—Code Release, [10.5281/zenodo.17536499](https://zenodo.org/record/17536499) (2025).