International Journal of Frontline Research in
Engineering and Technology
Journal homepage: https://frontlinejournals.com/ijfret/
ISSN: 2945-4840 (Online)

(RESEARCH ARTICLE)

A systematic analysis of data-driven signal processing for quantum sensing

Modou Njie *

University of Wisconsin-Madison, USA.

International Journal of Frontline Research in Engineering and Technology, 2026, 05(01), 015-023

Publication history: Received on 05 February 2026; revised on 12 March 2026; accepted on 14 March 2026

Article DOI: https://doi.org/10.56355/ijfret.2026.5.1.0013

Abstract

Quantum sensing offers sensitivities surpassing classical limits, yet practical deployment is often constrained by noise and inefficient signal extraction. This systematic review synthesizes literature from 2015 to 2025 and maps the landscape of data-driven signal processing across diverse platforms, including nitrogen-vacancy (NV) centers and cold atom interferometers. Emerging methodologies are categorized and emphasis is placed on the dominance of hybrid quantum-classical architectures where classical machine learning manages high-dimensional data processing while quantum processors execute specific primitives like feature mapping. Our findings demonstrate that advanced statistical frameworks such as Variational Bayesian Inference (VBI) enable scalable multi-parameter estimation with polynomial complexity, allowing dozens of sensor parameters to be estimated within minutes. Meanwhile, quantum sensing missions in GPS-denied navigation have achieved operational gains through AI-automated software designed to manage quantum hardware drifts and environmental noise, despite a persistent reality gap for generalized quantum machine learning. We further analyze the critical sensitivity-robustness dilemma inherent in entangled sensors and discuss mitigation strategies such as covariant quantum error-correcting codes. We also distinguish between theoretical Quantum Fisher Information (QFI) and realized Mean Squared Error (MSE) of sensor outputs to resolve benchmarking inconsistencies in quantum metrology, and propose a "Gold Standard" reproducibility framework tailored for the Noisy Intermediate-Scale Quantum (NISQ) era to promote automated workflows and hardware calibration transparency. This review provides a strategic roadmap for researchers to bridge the gap between theoretical sensitivity and reliable, software-defined operational utility in quantum sensing.

Keywords: Quantum Sensing; Quantum Machine Learning; Variational Bayesian Inference; Quantum Entanglement

1 Introduction

Quantum sensing leverages quantum coherence, entanglement and engineered probe states to measure physical parameters with sensitivities and resolutions that can surpass classical limits [1]. Over the last decade, quantum sensors based on platforms such as nitrogen-vacancy (NV) centers in diamond, trapped ions, cold atoms, superconducting circuits and photonic interferometers have moved from proof-of-principle demonstrations toward application-focused experiments in fields ranging from nanoscale magnetometry and biological imaging to inertial sensing and geophysics [1]. These devices ultimately produce classical measurement data such as photon counts, fluorescence signals, interferometric intensity measurements, or time-stamped readout sequences that depend on the sensor's quantum state [2]. However, realizing practical quantum sensing advantages requires confronting several data-centric challenges in which real sensor outputs are typically noisy and affected by platform-specific readout inefficiencies, drifts, non-Gaussian and nonstationary noise processes, and nonlinear encoding of information across correlated measurement outcomes [1,3]. These constraints complicate traditional estimation pipelines based on linear filters or simple maximum-likelihood estimators and can erode any nominal quantum advantage unless the full measurement-to-estimation chain accounts for these realities through appropriate signal-processing and data-analysis techniques [3].

* Corresponding author: Modou Njie.

In response, an expanding body of work has begun to treat quantum sensor outputs as data streams that benefit from modern, data-driven signal-processing and machine-learning approaches. Recent research demonstrates several complementary strategies. These include Bayesian and sequential-design methods to maximize information per shot and adaptively allocate measurements [4, 5]. In addition, there are variational and hybrid quantum-classical frameworks that jointly optimize probe preparation, measurement settings, and classical estimators in an end-to-end manner [3, 6]. Supervised or unsupervised learning models are also employed to denoise or classify physical parameters from high-dimensional measurement records where analytical likelihoods are unavailable or intractable [7, 8]. These techniques can improve sensitivity and robustness to realistic noise but their practical performance depends strongly on data volume, model choice, noise modelling, and the cost of training and deployment on experimental hardware [3, 6-8].

In the face of these barriers, the literature, at the same time, is heterogeneous in ways that hinder straightforward synthesis and cross-platform comparison. Studies vary in sensor platform, measurement modality, performance metrics (e.g., Fisher information or mean-squared error), data-preprocessing conventions, and reporting of training/validation protocols [2-5, 15-18, 20]. Moreover, papers differ in whether they evaluate methods using simulated noise models or with experimental datasets [3-4, 6-8]. They also differ in how they quantify computational or experimental costs [10,15]. This fragmentation limits the ability of practitioners to judge which data-driven signal-processing approaches are reliably effective for particular sensing tasks and under realistic operational constraints

Therefore, to clarify the evidence base and provide actionable guidance for researchers and experimentalists, we conduct a systematic review that synthesizes recent, high-quality literature (2015–2025) on data-driven signal processing for quantum sensor outputs. Our objectives are to map the landscape of quantum sensing platforms and the corresponding data modalities that arise in practice, and to categorize and compare data-driven signal-processing approaches applied to quantum sensors, including Bayesian/optimal-design, variational end-to-end frameworks, classical ML denoising/regression, and adaptive measurement policies. We identify common gaps in benchmarking, noise modelling, and reproducibility that impede fair comparison across studies. Finally, we propose standardized evaluation criteria and priority research directions to accelerate practical deployment of data-driven quantum sensing.

2 Methodology

This section outlines the methodological framework adopted to identify and synthesize relevant literature on data-driven signal processing for quantum sensor outputs. This ensures a comprehensive and transparent synthesis of findings.

2.1 Review Design

The study employs a systematic literature review methodology to consolidate and critically evaluate existing research on data-driven approaches applied to quantum sensing outputs. This design was selected to enable structured comparison across heterogeneous sensing platforms and analytical techniques, while minimizing selection bias. The review focuses on identifying recurring methodological patterns and unresolved challenges that shape the current state of the field.

2.2 Data Sources and Search Strategy

A comprehensive literature search was conducted across multiple scholarly databases commonly used for quantum science, signal processing, and applied machine learning research. These included ResearchGate, arXiv, and Physical Review Letters.

Search queries were constructed to reflect the intersection of quantum sensing and data-driven analysis. Representative keyword combinations included, but were not limited to:

- “quantum sensing” AND “signal processing”
- “quantum sensing” AND “machine learning”
- “Bayesian estimation” AND “quantum sensing”
- “variational quantum sensing”
- “denoising” OR “regression” AND “quantum measurement data”

2.3 Eligibility Criteria

Study selection followed a staged screening process consisting of title and abstract review, followed by full-text assessment. Only studies published between 2015 and 2025 were considered, reflecting the period during which data-driven methods became prominent in quantum sensing research. The study consisted of 28 research articles/technical reports.

2.3.1 Inclusion Criteria

Studies were included if they met the following conditions:

- Peer-reviewed journal articles, conference proceedings, preprints with substantial technical detail, or technical reports published between 2015 and 2025.
- Research addressing quantum sensing platforms such as NV centers, cold atoms, trapped ions, superconducting circuits, or photonic sensors.
- Studies proposing, implementing, or evaluating data-driven signal-processing techniques.
- Experimental, simulation-based, or hybrid studies reporting extractable performance metrics (e.g., sensitivity, robustness to noise).

2.3.2 Exclusion Criteria

The following were excluded from the review:

- Non-English publications.
- Papers published prior to 2015.

Purely conceptual or theoretical works that do not provide quantitative analysis, simulations, or experimentally relevant results.

Opinion pieces, editorials, or tutorial articles lacking original methodological or empirical contributions.

2.4 Data Extraction and Synthesis

For each included study, relevant information was extracted regarding the quantum sensing platform, data modality, signal-processing or learning approach employed, performance metrics used, and whether results were based on simulations, experiments, or both.

2.5 Ethical Considerations

This review relied exclusively on publicly available academic literature and did not involve personal data or proprietary datasets. Consequently, ethical approval was not required.

Figure 1 illustrates the PRSIMA flow diagram detailing the selection of articles for the review.

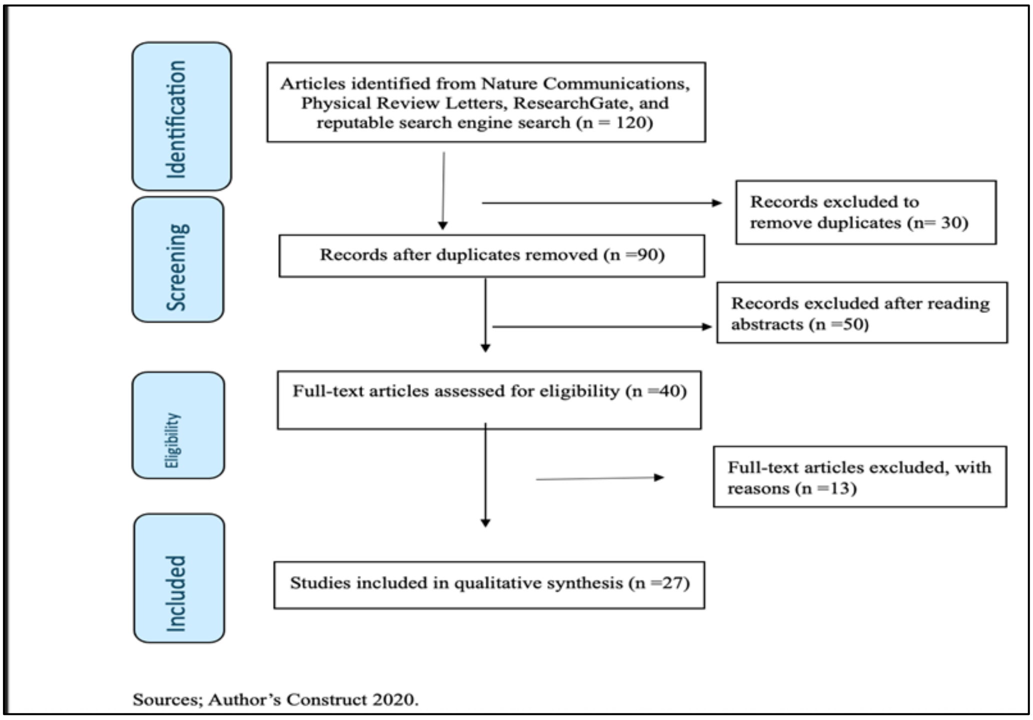

Figure 1 PRISMA Flow Diagram

3 Results

This section presents a synthesis of empirical evidence concerning the application of data-driven approaches such as quantum machine learning (QML) techniques to address signal processing challenges in modern quantum sensing platforms. The findings are categorized by methodology and quantitative performance benchmarking.

3.1 Categorization of Data-Driven Architectures and Sensor Modalities

3.1.1 Hybrid Quantum-Classical Learning Modalities and Architectures

Current research overwhelmingly emphasizes hybrid quantum–classical models in the pursuit of practical quantum solutions for sensor applications, particularly in metrology [9]. This architectural choice is necessitated by the limitations of current Noisy Intermediate-Scale Quantum (NISQ) hardware, which restricts the quantum processor's role to executing specific computational primitives, such as quantum feature mapping or kernel estimation [9, 10]. Mature classical ML techniques, including Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and various neural network architectures, are integrated to handle the bulk of data processing and optimization [10].

QML is specifically positioned to handle challenging signal processing tasks intrinsic to quantum systems, such as those characterized by high dimensionality, low sample counts, and time sensitivity [9]. The efficacy of these hybrid models, however, critically hinges on the process of quantum feature mapping (the translation of classical sensor output data into a quantum state) [10]. The difficulty and high resource cost associated with achieving high-fidelity encoding represent the central signal processing bottleneck, restricting the scalability and general applicability of QML models beyond academic proofs-of-concept. This constraint often necessitates restrictive assumptions about the input data structure for current quantum hardware, which ultimately limits the model's generality. A recent systematic review [11] observed that utility is not consistently supported in generalized application domains spanning from finance to medical image classification.

3.1.2 Signal Processing in Nitrogen-Vacancy (NV) Center Systems and Spectroscopy

Nitrogen-Vacancy (NV) centers in diamond , as pictured in figure 2, generate complex spectroscopic data based on fluorescence signals.

This data is essential for applications ranging from nanoscale magnetic imaging to fundamental molecular analysis. Extracting precise information from this complex signature necessitates advanced signal inversion and parameter estimation techniques and remains a priority [12]. Data-driven methods are employed not only for post-acquisition data processing but also for the optimization of the quantum control sequence (e.g., the MicroWave (MW) pulse sequence) [13]. The use of custom control programs allows for real-time adjustment of the instrument based on feedback, effectively transforming the signal processor into an adaptive control unit. This capability is critical for solid-state sensors where the limited coherence time T_2 necessitates optimizing the measurement protocol dynamically to maximize information gain before decoherence dominates the signal [14]. The fusion of signal processing and quantum control into a closed-loop system is essential for operational success in nitrogen-vacancy.

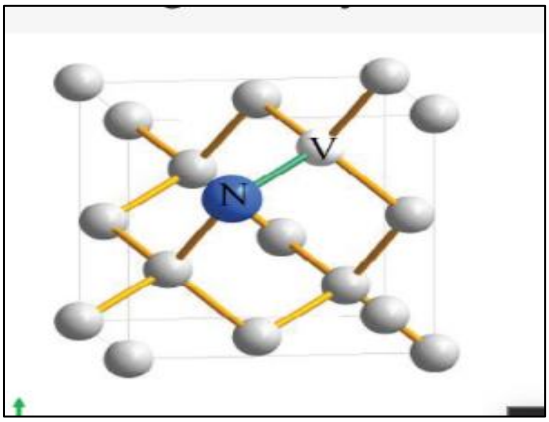

Figure 2 Schematic of NV center in diamond lattice. Reproduced from Jiazhao Tian et al., "Bayesian-Based Hybrid Method for Rapid Optimization of NV Center Sensors", Sensors 23(6), 3244 (2023), MDPI, under CC BY 4.0

3.2 Signal Processing in Cold Atom Interferometry

Cold atom quantum sensors, particularly interferometers, rely on the accurate measurement of atom clouds via Time-of-Flight (TOF) imaging. Techniques like Frequency Modulation Imaging (FMI) have demonstrated superior Signal-to-Noise Ratio (SNR) compared to Fluorescence Imaging (FI) for low optical depth [15], directly addressing the limitations imposed by atom detection noise in state-of-the-art interferometers.

3.3 Quantitative Performance Gains and Scalability Benchmarking

3.3.1 Empirical Demonstration of Scalability and Speed Gains via Advanced Signal Processing

VBI achieves computational tractability in high-dimensional quantum parameter spaces by approximating the intractable posterior distribution. This avoids the high variance and computational cost associated with exact sampling inference methods, which typically suffer from the "curse of dimensionality" [17]. VBI and its Sparse Bayesian Learning (SBL) variants are highly efficient for signal recovery in compressive sensing, particularly useful for reconstructing sparse or compressible signals from sub-Nyquist sampling [16]. VBI scales polynomially with the number of parameters, enabling the efficient estimation of dozens of parameters within minutes in experimental settings, such as identifying nuclear spins coupled to an electron spin quantum sensor [17]. Hybrid QML architectures enhance scalability by delegating data-intensive optimization and inference tasks to classical processors, while retaining quantum resources for state preparation, sensing, or feature generation. This division of labor has emerged as the dominant paradigm in quantum metrology and sensing, where near-term quantum hardware constraints preclude fully quantum learning pipelines [10]. This realization underscores that a significant portion of the immediate quantum advantage is derived not from a quantum circuit speedup, but from an algorithmic acceleration over conventional statistical techniques necessary for quantum system characterization.

Furthermore, within the Bayesian estimation paradigm, it is established that the minimum Mean Squared Error (MSE) estimator attains the lowest possible variance for a given prior probability and measurement operation [18]. This framework, which builds upon Personick's work, allows for the design of optimal measurement operators (Positive-Operator Valued Measures, or POVMs) that attain the minimum MSE. This provides a robust alternative to methods focusing purely on the Quantum Fisher Information (QFI) bound, offering a comprehensive strategy for measurement optimization that accounts for both the quantum state and the classical detection apparatus.

3.4 Comparative Analysis of Simulation and Experimental Hardware Performance (The Reality Gap)

A systematic review of generalized QML applications (e.g., digital health) reveals a substantial reality gap, finding no consistent trend to support empirical quantum utility when compared against established classical algorithms, especially when accounting for noise and hardware constraints [11]. However, this contrasts sharply with highly optimized, mission-specific applications. Commercial infrastructure software designed for managing quantum sensor outputs in dynamic environments has reported an operational advantage exceeding 100X compared to the best conventional baselines in GPS-denied navigation [19]. This stark contrast suggests that the path to commercial and operational utility is defined by the software layer that manages the quantum-classical interface. The significant performance gain is attributable to sophisticated AI automation embedded in the control software, which addresses crucial tasks such as real-time calibration, error suppression, and environmental modeling. Therefore, the current practical advantage in quantum sensing is best characterized as a "software-defined" operational gain, where robust signal processing and engineering management are the primary factors translating theoretical sensitivity into reliable field utility.

Table 1 Comparative Benchmarking of Empirical Performance Gains of Signal Processing Methods

Technique/Framework	Gain/Advantage Metric	Demonstrated Value	Advantage Type
General QML Algorithms	Empirical Utility	No consistent trend supporting Empirical Utility	Theoretical/Conceptual Promise (Utility Gap)
Variational Bayesian Inference (VBI)	Estimation Speed/Scalability	Estimation of Dozens of Parameters within Minutes (Polynomial Scaling)	Algorithmic Efficiency
Infrastructure Software Automation	Navigation Accuracy/Robustness	100X Improvement over Conventional Baseline	Operational/Engineering Gain

4 Discussion

This section provides an interpretation of the findings, focusing on the systemic challenges related to noise and robustness, and proposes strategic recommendations for future research in standardization and methodology

4.1 Interpreting Performance Disparity and the Operational Reality Gap

4.1.1 The Narrow Scope of Empirical Utility

The consistent observation that generalized QML algorithms fail to show a definitive, empirical quantum advantage in applications involving classical data, such as digital health [11], reinforces the conclusion that the inherent complexity and high overhead of quantum data encoding represent a primary obstacle [9]. The resources consumed and the noise introduced during the encoding process on NISQ hardware often outweigh the theoretical benefits of quantum computation. The data suggests that current quantum advantage is narrowly concentrated in intrinsically quantum tasks such as state characterization or adaptive control where the VBI methodology offers practical scalability gains [18].

4.1.2 Software Engineering as the Key to Operational Advantage

The immense operational gain demonstrated by software-managed quantum sensors (e.g., the >100X advantage in PNT) highlights that robust infrastructure software is the crucial intermediary required to translate high quantum sensitivity into reliable engineering utility [19, 20]. The function of this software is to execute AI automation for real-time noise modeling, hardware calibration, and dynamic error suppression. This recognition mandates a strategic shift in research focus toward developing this critical software layer, rather than focusing exclusively on abstract quantum algorithms that may not be robustly executable on current hardware.

4.2 The Challenge of Noise and Robustness

4.2.1 The Sensitivity-Robustness Dilemma in Quantum Sensing Using Entanglement

Entanglement is the quantum resource responsible for pushing the sensitivity of quantum sensors beyond classical and the standard quantum limit [21]. However, this heightened sensitivity is intrinsically linked to extreme vulnerability, as entanglement renders the system exquisitely susceptible to environmental disturbances such as stray magnetic fields, temperature fluctuations, and mechanical vibrations [22]. These environmental noise channels act as sources of decoherence, severely limiting the realized sensing gain [22]. Protecting the system's coherence against these external influences remains a fundamental challenge for both quantum sensing and related fields, such as quantum energy storage [23]. A significant theoretical solution proposes managing the sensitivity-robustness dilemma through the strategic design of entangled systems using covariant quantum error-correcting codes (CQEC) [22]. This strategy involves engineering the quantum sensor group to tolerate some noise-related errors by correcting the errors only approximately, rather than attempting resource-intensive exact correction.

4.3 Future Directions For Robustness to Sensitivity

The development of next-generation signal processing requires methods that integrate physical models. Physics-Informed Neural Networks (PINNs) represent a vital direction for future research, as they integrate known Hamiltonian physics and decoherence dynamics directly into the learning process [24]. This allows PINNs to learn control and signal processing policies that are inherently more generalizable and robust than those derived purely empirically, enhancing control efficiency and decoherence protection. Measurement-based feedback schemes, analogous to a classical Maxwell demon, must be refined and integrated with scalable estimation frameworks (such as VBI) to enable the precise, real-time control necessary for high-performance adaptive quantum sensing applications, particularly in metrology [17].

4.4 Establishing Standardized Benchmarking and Reproducibility

4.4.1 Recommendation: Adoption of Gold Standard Reproducibility Protocols

To move quantum sensing results into the realm of verifiable science, the field must adopt rigorous standards for computational reproducibility. The Gold Standard requires that the entire analysis, from data retrieval to final output generation, be automated and reproducible with a single command [25]. This necessitates thorough documentation of the order of analysis steps and the use of workflow management software to automate all components. Furthermore, all dependencies must be managed via a single-command setup, often implemented through containerization, to mitigate errors caused by differing operating systems or software versions. All random elements must be explicitly documented and set to deterministic seeds.

4.4.2 Recommendation: Quantum-Specific Reproducibility and Calibration Transparency

Table 2 Proposed Gold Standard Reproducibility Checklist for Data-Driven Quantum Sensing

Requirement Category	**Gold Standard Criterion**	**Implementation for Quantum Sensing**	**Justification**
Code and Models	All analysis automated with a single command	Use workflow managers to automate data retrieval, quantum data preprocessing, QML training, and figure generation.	Verifies end-to-end functionality across the hybrid quantum-classical pipeline
Computational Environment	The complete computational environment is reproducible through a single environment initialization command	Use containerization or environment managers to explicitly define the operating system, programming language version, quantum SDKs, simulators, and all auxiliary libraries	Mitigates environment-specific computational errors and version conflicts
Data and Determinism	All random elements set to deterministic seeds.	Publication of classical algorithm seeds and quantum simulation parameters (e.g., random circuit depths, noise realizations)	Ensures that observed performance is a robust feature, not a stochastic artifact of the training initialization.
Quantum Hardware Specification	Key experimental and modeling details recorded	Publication of the exact quantum hardware calibration data (noise models, T_1 / T_2 values) or parameters used for noisy simulation	Essential for validating results obtained on cloud-based NISQ devices and bridging the reality gap

For data-driven quantum sensing, the standard reproducibility requirements must be augmented to account for the unique characteristics of NISQ hardware. Because quantum processors are noisy and exhibit temporal drift, a third party cannot reliably reproduce claimed performance gains without explicit knowledge of the experimental conditions [26]. Therefore, achieving trust in results demands the mandatory publication of the exact quantum hardware calibration data used during experiments or noisy simulations [27]. This includes parameters such as measured T_1 and T_2 coherence times, gate fidelities, and the specific parameters used to model noise. This calibration transparency is essential for validating results obtained on cloud-based quantum systems and is a critical step in bridging the reality gap between simulation and deployment. Finally, the community needs to establish standardized, public dynamic benchmark datasets to enable rigorous and comparative evaluation across different machine learning strategies.

5 Conclusion

Data-driven signal processing has proven to be an indispensable layer for translating the theoretical advantages of quantum mechanics into reliable sensor performance. The current state of the field is defined by the necessary use of hybrid quantum-classical architectures, which have successfully demonstrated scalable and rapid parameter estimation capabilities, particularly through advanced statistical frameworks such as Variational Bayesian Inference (VBI). While fundamental metrology experiments validate the promise of entanglement-enhanced sensitivity, the most significant realized gains in operational performance have been achieved through sophisticated infrastructure software that employs AI for real-time control and error management.

Future work should prioritize achieving quantum advantage in computational sensing through the combined efficiency of algorithms (VBI) and robust engineering practices (software automation, CQEC), rather than pursuing purely exponential computational speedup. The quantum sensing community should focus on standardizing the scientific process by resolving the metric incoherence between QFI and MSE and enforcing rigorous Gold Standard reproducibility protocols. We recommend prioritizing the development of physics-informed adaptive control systems and mandatory calibration transparency to accelerate the transition of quantum sensors into reliable commercial technologies across critical infrastructure and scientific research.

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