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PRISMA-Guided Systematic Review of IOT-Based Smart Healthcare Monitoring and ML Heart-Disease Risk Assessment

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Abstract— Smart-healthcare monitoring joins Internet of Medical Things (IoMT) sensing with machine learning (ML) for risk assessment, but the evidence is split across architecture, security and prediction studies. This paper presents a PRISMA 2020-guided systematic review of 30 peer-reviewed journal studies (2019–2025) on IoT patient monitoring, ML heart-disease prediction, or both. From a 31-record reference list, one dataset record was excluded and 30 studies were included. Each study was coded for design, primary theme and seven capabilities, then synthesised qualitatively. Of the 30 studies, 6 are systematic reviews, 9 are surveys, 9 are system studies and 6 are ML prediction studies; 18 (60%) appeared in 2022–2024 and 15 (50%) in IEEE Access. ML was a core component in 15 studies and sensing in 8, but only 4 integrate sensing and ML in one system, and none reports a hardware-free virtual-sensor simulation. Five research gaps follow: hardware and cloud dependence, scarce integrated pipelines, mismatch between monitored vital signs and benchmark dataset attributes, inconsistent evaluation reporting, and limited security and outcome evidence in prototypes. The review supports a software-only IoMT prototype paired with a separate, leakage-aware ML benchmark. Findings are qualitative, single-reviewer and limited to the curated corpus.

Index Terms— *Internet of Medical Things, machine learning, heart-disease prediction, PRISMA, remote patient monitoring, systematic review, virtual sensors.*

I. INTRODUCTION

Connected medical devices now let clinicians review a patient's physiological signals outside the hospital. Recent work on this theme includes digital-twin-assisted remote monitoring with machine learning [1], reviews of IoT patient-monitoring architectures and open issues [2], wearable IoMT with cloud-edge artificial intelligence [3], the components of wireless healthcare monitoring [4], and the enabling technologies of biomedical IoT [5]. Because the data are sensitive, surveys of IoMT security and privacy [6] and of deep-learning-assisted protection [7] treat confidentiality as a design requirement rather than an add-on.

Implementations vary widely. Reported systems include a rigid-flex wearable sensor patch [8], an Arduino and NodeMCU model for rural and urban settings [9], an MQTT-broker system for prehospital vital-sign monitoring [10], an AIoT activity-tracking system [11], IoT with cloud-based classification [12], real-time cloud storage of patient data [13] and chronic-patient monitoring with big data [14]. Reviews add accessible IoT technology [15], quality-of-life outcomes [16], non-invasive vital-sign acquisition [17] and fitness-oriented wearables [18].

Two further bodies of evidence frame clinical value and analytics. Systematic reviews of AI for smart health devices [19] and of remote patient monitoring on safety, adherence, quality of life and cost [20] describe use and impact. In parallel, reviews of ML for heart-disease diagnosis [21], cardiovascular prediction from medical big data [22] and combined ML and IoT monitoring [23] sit beside model studies that use feature selection [24], integrated pipelines [25], hybrid techniques [26], e-healthcare classification [27], stacking with balancing [28] and deep-learning decision support [29]. One study joins wearable IoT and deep learning for monitoring and heart-disease prediction [30].



These strands are rarely read together. A reader must reconcile hardware-heavy prototypes, security surveys and dataset-specific classifiers to judge what a reproducible, low-cost monitoring-and-prediction study should contain. This paper applies the PRISMA 2020 reporting guideline [31] to the 30 studies above to make that comparison explicit.

The review addresses four questions:

- **RQ1.** Which IoMT architectures, components and protocols are used for patient monitoring, and what limits them?
- **RQ2.** Which ML approaches are used for heart-disease prediction, and how are they evaluated?
- **RQ3.** How are sensing, ML and security combined in integrated systems?
- **RQ4.** What gaps remain for a reproducible, hardware-free monitoring-and-prediction study?

The contributions are: (i) a PRISMA-guided protocol, eligibility criteria and flow diagram for the 30-study corpus (Section II, Fig. 1); (ii) a descriptive map of the corpus by year, design, theme and capability (Section III, Figs. 2–4); (iii) a thematic synthesis and 30-study comparison table (Sections IV and V); and (iv) five evidence-based research gaps with a future-work agenda (Section VI). Limitations and conclusions follow in Sections VII and VIII.

II. REVIEW METHODOLOGY

A. Protocol and Reporting Standard

The review follows the PRISMA 2020 statement [31]. No protocol was registered in advance, so the methods below record what was done, not a pre-specified plan.

B. Eligibility Criteria

A record was eligible if it met every inclusion criterion in Table I.

TABLE I. ELIGIBILITY CRITERIA FOR THE REVIEW

Domain	Inclusion	Exclusion
Topic	IoT or IoMT patient or health monitoring; ML prediction of heart or cardiovascular disease; or the integration of the two	Studies unrelated to health monitoring or cardiovascular prediction
Record type	Peer-reviewed journal article: primary study, survey or systematic review	Datasets and repository entries, grey literature, conference abstracts
Period	Published 2019–2025	Published before 2019
Language	English	Other languages
Content	Reports an architecture, method, evaluation or evidence synthesis	Records with no methodological or evidential content

C. Information Sources and Search

Records were gathered by the author through targeted literature searching while preparing an M.Tech synopsis. The 30 included studies appeared in 14 outlets, led by IEEE Access (15 studies); the rest are in IEEE Internet of Things Journal, Emergency Medicine International, Journal of Healthcare Engineering, Journal of Big Data, PLOS ONE, Health Informatics Journal, BioMedical Engineering OnLine, Healthcare (2), Sensors (2), PeerJ Computer Science, npj Digital Medicine, Artificial Intelligence in Medicine, and Medical Engineering & Physics. Search strings, dates and per-database hit counts were not logged. PRISMA identification counts (records identified, duplicates removed) therefore cannot be reported, and the flow diagram starts from the project reference list. This is listed as a limitation in Section VII.

D. Selection Process

The author screened all 31 records against Table I on record type, period and topic, then assessed the 30 remaining journal articles against the content criterion. One record, the UCI Heart Disease dataset entry [32], was excluded because it is a data source, not a study, and dates from 1989. No other record was excluded. Fig. 1 shows the flow.

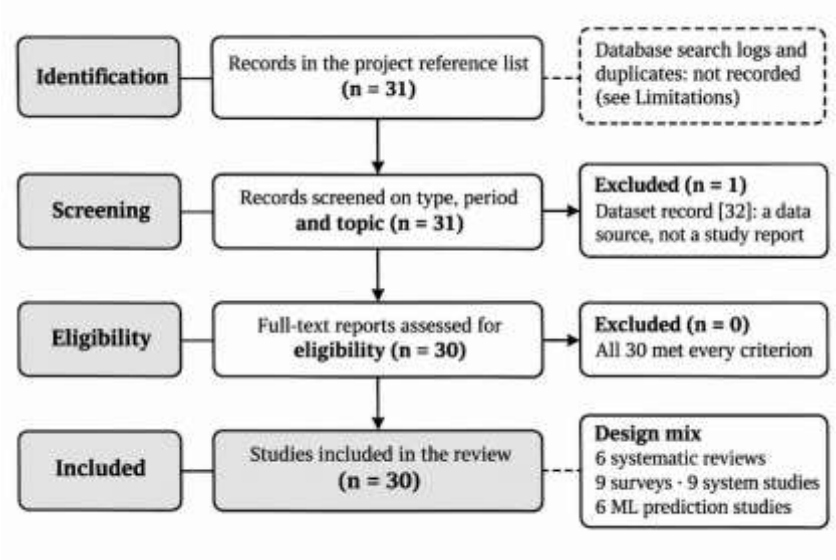


Fig. 1. PRISMA 2020-style flow diagram of record screening and inclusion.

E. Data Collection and Items

One reviewer extracted, for each study, the year, venue, design, primary theme, core contribution and limitation. Extraction used each study's title, abstract and the summaries compiled during synopsis preparation, and it was not independently duplicated. Design was coded as systematic review, survey, system study or ML prediction study. Primary theme was coded as one of seven mutually exclusive categories (Section III). Seven capabilities were coded present or absent, with several allowed per study:

- **C1.** Sensing and data acquisition
- **C2.** Communication protocols or networks
- **C3.** Cloud, big-data or storage back end
- **C4.** ML as a core component
- **C5.** Security or privacy
- **C6.** Sensing and ML combined in one reported system or framework
- **C7.** Hardware-free virtual-sensor simulation

F. Quality Appraisal

No formal risk-of-bias instrument was applied, because the corpus mixes reviews, system descriptions and prediction models that no single tool fits. Appraisal was limited to peer-review status, venue type and relevance to the four review questions. Reported accuracy figures were not re-verified, and the review does not rank studies by performance.

G. Synthesis Methods

Studies were synthesised narratively by theme (Section IV) and compared in tables (Section V). Counts and percentages in Section III are simple tallies of the coded variables over n = 30. No meta-analysis was attempted: outcome measures, datasets and populations differ across studies, so pooling would mislead.

III. RESULTS

A. Study Selection

Of 31 records screened, 30 met every criterion and were included (Fig. 1). Output is concentrated in 2022–2024, which holds 18 of 30 studies (60%), with a peak of 8 in 2022 (Fig. 2). Half of the studies (15) appeared in IEEE Access.

B. Study Characteristics

Four designs appear in similar proportions: 9 surveys (30%), 9 system studies (30%), 6 systematic reviews (20%) and 6 ML prediction studies (20%). Reviews and surveys together make up 15 studies (50%), so half the corpus describes the

field rather than tests a method. All six ML prediction studies [24]–[29] were published in IEEE Access between 2019 and 2023.

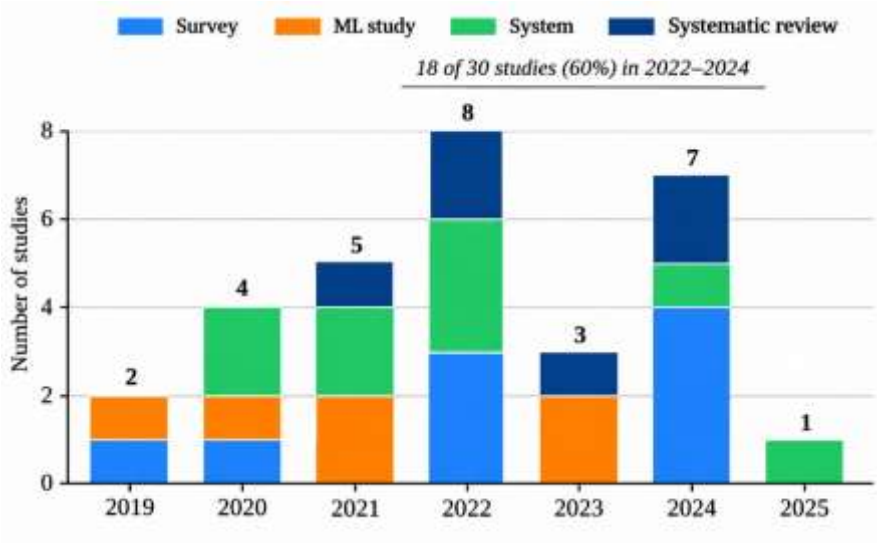


Fig. 2. Included studies by publication year and design (n = 30).

C. Thematic Distribution

Each study was assigned one primary theme (Fig. 3). Architecture, components and surveys is the largest theme (7 studies). Integrated IoT-and-ML systems number four [1], [11], [12], [30], and security and privacy is the smallest with two [6], [7].

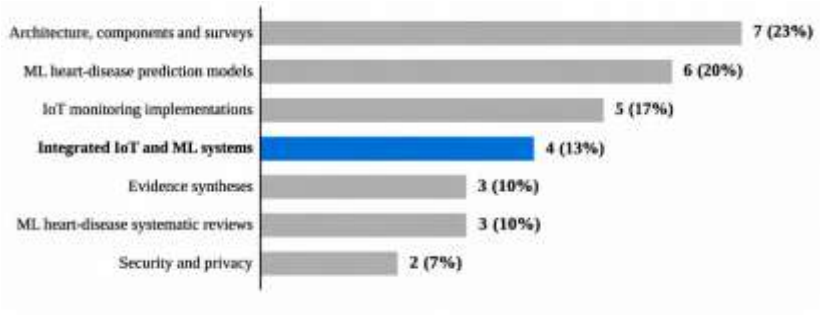


Fig. 3. Included studies by primary theme (n = 30).

IV. LITERATURE REVIEW AND THEMATIC SYNTHESIS

The 30 studies fall into seven themes. The synthesis below answers RQ1–RQ3 and sets up the comparison in Section V.

A. Architecture, Components and Surveys

Seven studies map the IoMT landscape [2]–[5], [15]–[17]. A review of IoT patient monitoring covers monitored parameters, networks, protocols and open research issues [2]. The review in [3] covers wearable IoMT with cloud-edge AI and federated learning, and stresses data quality, privacy and edge constraints. Reference [4] organises wireless healthcare monitoring into sensors, data collection, processing and networks, while [5] surveys enabling technologies, applications and challenges and points to deployment and regulatory barriers. Cost and access are the focus of [15], which pairs a review with an experimental design for accessible IoT. Reference [16] reviews IoT healthcare monitoring broadly, and [17] reviews non-invasive vital-sign acquisition and its limits. These surveys agree on a layered pattern of sensing, communication and processing. Apart from the experimental design in [15], they are reviews, so none supplies a complete lightweight implementation (RQ1).

B. Security and Privacy

Two surveys treat security directly. Reference [6] surveys security and privacy challenges in IoMT-enabled healthcare, and [7] surveys deep-learning-assisted security and privacy provisioning. Both show that confidentiality is a first-order



requirement. The cloud-edge review [3] and the integrated system in [30], which uses secure transmission, make the same point from the design side. Security appears in only four of the 30 studies (13%; Fig. 4).

C. IoT Monitoring Implementations

Five studies describe working or proposed monitoring systems [8]–[10], [13], [14]. Reference [8] presents a rigid-flex wearable sensor patch for IoT-connected healthcare. Reference [9] builds a ubiquitous monitoring model for rural and urban areas from Arduino, NodeMCU and GSM modules and several health parameters. Reference [10] uses an MQTT broker for individual vital-sign monitoring in emergency or prehospital use. Reference [13] covers patient health tracking with big-data storage on real-time cloud computing, and [14] applies big data and IoT to remote monitoring of chronic patients. Two dependencies recur: physical hardware [8], [9] and cloud infrastructure [13], [14] (RQ1).

D. Integrated IoT and ML Systems

Four studies combine monitoring with ML [1], [11], [12], [30]. Reference [1] evaluates six ML algorithms inside a digital-twin framework for remote patient monitoring, using public and provider data. Reference [11] tracks patient activity with AIoT, and [12] combines an IoT platform, cloud computing and an LSTM to monitor and classify patients. Reference [30] joins wearable IoT, secure transmission and a modified neural network for monitoring and heart-disease prediction. Each adds complexity, from twin architectures and physical data collection to cloud services and deep models, which makes reproduction hard for a student or a small laboratory (RQ3).

E. Evidence Syntheses

Three systematic reviews place the technology in context. Reference [18] examines wearables and IoT for fitness assessment, [19] reviews AI approaches for smart health devices, and [20] synthesises 29 studies on how remote patient monitoring affects safety, adherence, quality of life and cost. The last matters for prototype work: outcomes of this kind need clinical deployment, so a software prototype cannot claim them.

F. Machine Learning for Heart-Disease Prediction

Three systematic reviews [21]–[23] and six model studies [24]–[29] address RQ2. The reviews cover ML-based heart-disease diagnosis [21], ML for cardiovascular prediction from medical big data [22], and the combination of ML and IoT in cardiovascular monitoring [23]. References [21] and [22] caution that datasets differ in features and populations, so results do not transfer freely. Reference [23] bridges IoT and prediction and supports treating monitoring data and prediction data as separate tasks.

Among the model studies, [24] applies Relief and LASSO feature selection, [25] builds an integrated pipeline with preprocessing and feature analysis, [26] uses hybrid techniques, [27] pairs classifiers with feature selection for e-healthcare, [28] stacks models with balancing and dimensionality reduction, and [29] applies dense deep-learning models across datasets. Reported results in [25] and [26] are dataset-specific, and [27] stresses validation. The UCI Heart Disease dataset [32], with 303 instances and 13 predictive attributes in its commonly used Cleveland subset, is a public benchmark against which such models can be compared.

V. COMPARATIVE ANALYSIS

Table II compares the 30 studies by year, design, primary theme, contribution and noted limitation. Themes are abbreviated as Architecture (architecture, components and surveys), Security, Implementation (IoT monitoring implementations), Integrated (integrated IoT and ML systems), Evidence (evidence syntheses), ML review and ML model.

TABLE II. COMPARISON OF THE 30 INCLUDED STUDIES

Ref.	Year	Design	Theme	Core contribution	Limitation or note
[1]	2025	System	Integrated	Six ML algorithms with a digital twin; public and provider data	Complex twin architecture; physical data collection
[2]	2024	Survey	Architecture	Parameters, networks, protocols and open issues	Review only; no prototype



[3]	2024	Survey	Architecture	Cloud-edge AI and federated learning for wearables	Advanced for a lightweight build; data quality and privacy issues
[4]	2024	Survey	Architecture	Taxonomy of sensors, collection, processing and networks	No single lightweight implementation
[5]	2022	Survey	Architecture	Enabling technologies and layered architecture	Deployment and regulatory barriers
[6]	2019	Survey	Security	IoMT security and privacy challenges	Advanced mechanisms not implemented
[7]	2024	Survey	Security	Deep-learning-assisted security and privacy	Survey, not a deployable system
[8]	2020	System	Implementation	Rigid-flex wearable sensor patch	Hardware-based acquisition
[9]	2022	System	Implementation	Arduino, NodeMCU and GSM; several parameters and patient history	Requires physical hardware
[10]	2022	System	Implementation	MQTT broker for individual vital-sign monitoring	Broker-based deployment; software-only simulation not examined
[11]	2022	System	Integrated	AIoT patient activity tracking	Broader activity scope than core vital signs
[12]	2021	System	Integrated	IoT, cloud and LSTM for monitoring and classifying	LSTM and cloud add complexity
[13]	2024	System	Implementation	Patient tracking with big-data storage on real-time cloud	Cloud infrastructure dependency
[14]	2021	System	Implementation	Chronic-patient monitoring with big data and IoT	Broad deployment context
[15]	2020	Survey	Architecture	Review and experimental design for accessible IoT	Accessibility and cost focus
[16]	2022	Survey	Architecture	IoT healthcare monitoring and quality of life	Broad background; no implementation
[17]	2022	Survey	Architecture	Non-invasive vital-sign acquisition	Limits of non-invasive sensing
[18]	2021	Syst. review	Evidence	Wearables and IoT for fitness assessment	Not a cardiac diagnostic benchmark
[19]	2024	Syst. review	Evidence	AI approaches for smart health devices	Does not validate a specific model
[20]	2024	Syst. review	Evidence	Remote patient monitoring outcomes (29 studies)	Outcomes need clinical deployment
[21]	2022	Syst. review	ML review	ML heart-disease diagnosis	Dataset heterogeneity
[22]	2022	Syst. review	ML review	ML for cardiovascular prediction from medical big data	Datasets differ in features and populations
[23]	2023	Syst. review	ML review	ML and IoT for cardiovascular prediction and monitoring	Review; no implementation
[24]	2021	ML study	ML model	Relief and LASSO feature selection	Feature-selection emphasis



[25]	2021	ML study	ML model	Integrated pipeline with preprocessing and feature analysis	Results not transferable without retesting
[26]	2019	ML study	ML model	Hybrid ML techniques	Results dataset-specific
[27]	2020	ML study	ML model	Classifiers with feature selection for e-healthcare	Stresses validation
[28]	2023	ML study	ML model	Stacking with balancing and dimensionality reduction	Complex ensemble design
[29]	2023	ML study	ML model	Dense deep-learning decision support across datasets	More complex than simple baselines
[30]	2020	System	Integrated	Wearable IoT, secure transmission, modified neural network	Hardware, security and deep-learning complexity

Table III lists which studies were coded for each capability, and Fig. 4 counts them.

TABLE III. STUDIES CODED FOR EACH CAPABILITY

Capability	Studies coded
C1 Sensing and acquisition	[1], [3], [4], [8], [9], [17], [18], [30]
C2 Communication and networks	[2], [4], [9], [10], [30]
C3 Cloud and storage	[3], [12], [13], [14]
C4 ML as a core component	[1], [3], [11], [12], [19], [21]–[30]
C5 Security and privacy	[3], [6], [7], [30]
C6 Sensing and ML in one system	[1], [11], [12], [30]
C7 Hardware-free virtual-sensor simulation	None

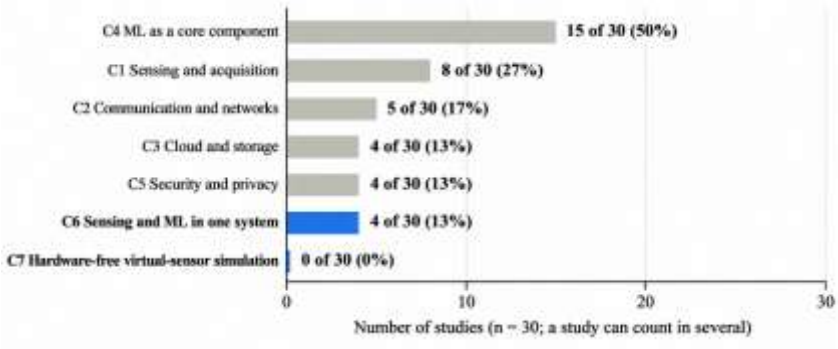


Fig. 4. Number of included studies addressing each capability (n = 30; a study may count in several).

Three patterns emerge. First, ML is the most common core component (15 of 30, 50%) and sensing the second (8, 27%), while communication (5), cloud or storage (4), security (4) and integration (4) each cover 17% or less. Second, the four integrated systems each carry heavy infrastructure: a digital twin [1], AI-based activity tracking [11], cloud services with an LSTM [12], or wearable hardware with secure transmission [30]. Third, no study was coded for hardware-free virtual-sensor simulation (C7). This is a statement about the 30 coded studies, not about the literature at large.



VI. RESEARCH GAPS AND FUTURE DIRECTIONS

The comparison supports five gaps (RQ4). Each is tied to evidence in the corpus and to a direction that a reproducible study can take, as Table IV shows.

TABLE IV. RESEARCH GAPS, EVIDENCE AND PROPOSED DIRECTIONS

Gap	Evidence in the corpus	Consequence	Proposed direction
G1. Hardware and cloud dependence	No study coded C7; acquisition relies on patches and microcontrollers [8], [9]; cloud back ends in [13], [14]	Cost and setup make replication hard for small laboratories	Software-only virtual-sensor pipeline with local storage
G2. Few integrated pipelines	Four of 30 studies [1], [11], [12], [30], each with heavy infrastructure	Hard to tell which component drives a result	Lightweight end-to-end pipeline with modular parts
G3. Monitored vitals do not match benchmark attributes	Dataset heterogeneity [21], [22]; separate data and prediction tasks supported by [23]	Simulated vitals could be fed to a model trained on unrelated clinical attributes	Two separate streams: simulated monitoring, and a benchmark screening module that uses only documented attributes [32]
G4. Inconsistent evaluation and complexity-first design	Dataset-specific results [25], [26]; validation stressed in [27]; ensembles and deep models in [28], [29]	Results are hard to compare across studies	Reproducible baselines, stratified splits, leakage-aware preprocessing and a fixed metric set
G5. Limited security and outcome evidence in prototypes	Security in four of 30 studies [3], [6], [7], [30]; outcome evidence needs deployment [20]	Prototypes may overclaim clinical value	Synthetic patient identifiers, access separation and an explicit non-clinical scope

Taken together, the gaps point to a software-only IoMT prototype that generates time-stamped vital signs from virtual sensors, applies configurable alert rules, and stores and displays the data, paired with a separate ML benchmark on a public heart-disease dataset. The prototype would then be evaluated under controlled scenarios such as different patient counts, missing-data rates and simulated delays.

Future work should:

- validate the simulated stream against real sensor traces before any clinical claim;
- test the ML module on external cardiovascular datasets and report calibration, not only discrimination;
- add access control and encryption to the software pipeline, following the security surveys [6], [7];
- log search strings, dates and per-database counts so that a full PRISMA identification stage can be reported in an update of this review.

VII. DISCUSSION, THREATS TO VALIDITY AND LIMITATIONS

A. Answers to the Review Questions

- **RQ1.** IoMT monitoring is described as layers of sensing, communication and processing [2]–[5]. Implementations depend on physical hardware [8], [9] or cloud back ends [13], [14], and surveys call out data quality, privacy and regulatory barriers [3], [5].



• **RQ2.** Heart-disease prediction studies use feature selection, hybrid methods, stacking and deep learning [24]–[29]. Reported results are dataset-specific [25], [26], and reviews warn of dataset heterogeneity [21], [22].

• **RQ3.** Only four studies join sensing and ML [1], [11], [12], [30], and each adds a digital twin, cloud services, deep models or specialised hardware.

• **RQ4.** Five gaps remain (Table IV), led by the absence of a hardware-free, reproducible monitoring-and-prediction design.

B. Threats to Validity and Limitations

• **Single reviewer.** One person screened and coded all records, with no independent check, so coding errors and bias cannot be ruled out.

• **Curated corpus.** The 30 studies come from targeted searching, not a logged multi-database search. PRISMA identification counts are missing, and relevant studies may be absent. The gap findings hold for this corpus only.

• **Extraction depth.** Coding used titles, abstracts and compiled summaries, not a full-text re-read of every study.

• **No risk-of-bias tool.** Study quality was not scored, and reported accuracy was not re-verified.

• **Scope.** Only English-language journal articles from 2019–2025 were eligible, so conference papers and grey literature are excluded.

• **Qualitative synthesis.** No meta-analysis was possible, and capability counts describe coverage, not effectiveness.

These limits mean the review is best read as a structured map of a defined corpus that motivates a design, not as an exhaustive survey of the field.

VIII. CONCLUSION

This PRISMA-guided review mapped 30 peer-reviewed studies on IoT patient monitoring and ML heart-disease prediction. The corpus is recent (60% from 2022–2024), evenly split across surveys, system studies, systematic reviews and ML prediction studies, and strong on ML (15 studies) but thin on integration (4 studies). None of the 30 studies reports a hardware-free virtual-sensor simulation. The five gaps in Table IV support a software-only IoMT prototype with configurable alerts, paired with a separate and leakage-aware ML benchmark, as a reproducible next step. A logged multi-database search, independent double screening and a full-text appraisal would strengthen a future update.

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