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*Review Article*

# A Review of AI-Wearable Technologies for Public Health Surveillance in the U.S: Challenges and Recommendations

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## About Article

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**ABSTRACT**

Artificial intelligence (AI)–enhanced wearables generate continuous physiologic streams that can be aggregated for real-time public health surveillance. This review summarizes evidence from U.S. studies on device penetration, analytic performance, and operational value. Surveillance infrastructure has evolved from mailed case cards to cloud dashboards accepting patient-generated data; current machine-learning pipelines transform inertial, photoplethysmographic, and temperature signals into population biomarkers. Lead-time gains of two to six days over laboratory reporting have been documented for influenza, COVID-19, and heart failure admissions. However, uneven adoption, sensor bias, privacy regulation, and limited interoperability constrain scale-up. Interfacing solutions such as FHIR subscriptions and federated analytics are assessed, alongside emerging FDA guidance on AI lifecycle management. Strategic recommendations address standards consolidation, equitable subsidization of devices, algorithm auditability, and workforce training. With these measures, AI wearables could transition from consumer novelties to an integral layer of U.S. public-health intelligence, offering earlier outbreak detection, finer chronic-disease surveillance, and more precise resource allocation.

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## 1. INTRODUCTION

Public health surveillance in the United States has always traveled with technology. Paper case cards mailed to state epidemiologists dominated the early twentieth century; telephone hotlines, faxed laboratory slips, and electronic laboratory reporting each arrived as communications matured. Yet these upgrades still captured illness only after citizens sought care. The first real-time shift came when internet search logs and social media chatter were mined for influenza signals, illustrating that data created for non-clinical reasons could illuminate population health. Wearable devices represent a further, more intimate step along that continuum. A 2019 Pew Research Center survey reported that roughly one in five American adults already wore a smartwatch or fitness tracker on most days (Vogels, 2020). Longitudinal analyses show adoption climbing steadily through the pandemic years, with nationally representative polling in 2022 indicating well over one-third of adults now engage with wearables at least weekly (Chandrasekaran *et al.*, 2025).

Who wears these devices, however, is not evenly distributed. A cross-sectional study of U.S. adults with, or at heightened risk for, cardiovascular disease found uptake markedly lower among older, less educated, and lower-income groups compared with their younger, wealthier peers (Dhingra *et al.*, 2023). This demographic skew raises immediate questions about representativeness whenever wearable data are extrapolated to entire communities.

Technological capability has advanced just as quickly. In 2018, the U.S. Food and Drug Administration granted a de novo clearance to Apple's irregular-rhythm notification algorithm, the first consumer-facing software permitted to flag atrial fibrillation from photoplethysmography alone (FDA, 2018). The accompanying Apple Heart Study demonstrated both the reach and the limitations of large-scale, app-based cardiovascular screening, enrolling hundreds of thousands of participants without a single clinic visit (Campion & Jarcho, 2019). Parallel investigations used de-identified Fitbit streams to improve real-time state influenza estimates, shaving precious days off traditional reporting lags (Radin *et al.*, 2020). During the first waves of COVID-19, the Scripps DETECT project showed that aggregated deviations in resting heart rate and sleep could foreshadow regional case spikes, hinting at a role for wearables as early-warning radar (DETECT, n.d.).

Policy ecosystems are beginning to adapt. The Centers for Disease Control and Prevention has folded exploratory consumer-device pilots into its Data Modernization Initiative, an effort to knit disparate digital sources into a cohesive national surveillance fabric (CDC, 2024c). Meanwhile, the Centers for Medicare & Medicaid Services introduced new remote-physiological-monitoring billing codes, signaling that patient-generated data are viewed not merely as curiosities but as reimbursable components of care (HealthSnap, 2022).

There is still a large room for improvement. Wearable algorithms validated largely in affluent, lighter-skinned cohorts may misclassify signals when deployed across America's full diversity, a concern underscored by recent reports of bias in optical sensing accuracy (Jeong *et al.*, 2025). Moreover, the sheer torrent of time-series data tests the storage, analytic, and workforce capacities of public health agencies already stretched by legacy system upkeep.

### 1.1. Research questions

To what extent can AI-enhanced wearable devices provide earlier, more representative, and operationally actionable intelligence for U.S. public health surveillance and health system planning?

### 1.2. Working hypothesis

When integrated with existing surveillance infrastructure under rigorous interoperability, privacy, and equity safeguards, wearable-derived signals will (i) deliver clinically meaningful lead times relative to laboratory-based reporting and (ii) improve resource-allocation forecasts without exacerbating existing health disparities.

To address this question, the review (i) synthesizes AI techniques embedded in current wearables, (ii) catalogues documented public-health use cases, (iii) evaluates impacts on health-system planning, (iv) analyzes technical, ethical, and regulatory challenges, and (v) proposes strategic pathways for equitable adoption. By situating AI-enhanced wearables within the broader evolution of U.S. surveillance infrastructure, the analysis clarifies both the potential benefits and the guardrails necessary for responsible implementation.

## 2. LITERATURE REVIEW

Academic commentary on AI-enhanced wearables has accelerated since 2019, yet the evidence remains scattered across clinical, informatics, and public health outlets. The first robust hint that consumer sensors might serve epidemiology arrived during the 2017-18 U.S. influenza season, when Radin *et al.* demonstrated that statewide deviations in resting heart rate and sleep among 47,000 Fitbit users improved influenza-like-illness forecasts by up to one-third compared with historic baselines (Radin *et al.*, 2020). That proof-of-concept sparked a broader literature interrogating whether "small" personal data could be safely scaled into "big" population surveillance. A 2021 systematic scoping review of 755 digital-surveillance studies, however, found that fewer than 2% had incorporated wearable streams; most relied instead on search or social-media signals, and only 0.8% were embedded in real-world public-health practice (Shakeri Hossein Abad *et al.*, 2021).

COVID-19 acted as both a catalyst and a stress test. Gunasekeran *et al.* catalogued 247 digital health tools deployed during the pandemic and noted that wearables, while prominent in headlines, remained underevaluated compared with telehealth or AI triage software (Gunasekeran *et al.*, 2021). Even so, small observational studies suggested promise: Aggregated smartwatch data detected county-level COVID-19 case surges several days before laboratory confirmation, and machine-learning models that combined those biometrics with symptom logs increased diagnostic yield six-fold in targeted testing campaigns.

Parallel scholarship has mapped who actually wears the devices. A cross-sectional National Health Interview Survey analysis showed that just 18% of U.S. adults with established cardiovascular disease used a wearable in 2019-20, versus 29%

of the general population; uptake plunged with age, lower income, and limited formal schooling (Dhingra *et al.*, 2023). Such demographic skews warn that raw sensor streams may amplify health-equity gaps if used uncritically.

Economic evidence lags behind technical enthusiasm. A 2024 systematic review conducted by Velasquez *et al.* (2024) identified only 18 cost-effectiveness studies; however, most of these studies reported gains in quality-adjusted life-years and, in several chronic disease contexts, net cost savings when wearables facilitated early intervention (Velasquez *et al.*, 2024). Still, heterogeneity in methodology and short follow-up periods preclude definitive conclusions.

Device-level validation has grown more ambitious. The Apple Heart Study enrolled 419,000 volunteers and reported a positive predictive value of 0.84 for atrial-fibrillation alerts, establishing the feasibility of virtual mega-cohorts while reminding skeptics that only 0.5% of users were ever flagged, a figure that tempers hopes of blanket screening (Perez *et al.*, 2019). Yet pragmatic trials that pipe such insights into health-system workflows or measure downstream outcomes like avoided admissions remain rare.

Overall, the literature portrays AI wearables as a tantalizing but still experimental asset for public health, rich in pilot data, lean in implementation science, and urgently in need of equity-aware scaling strategies. Table 1 summarizes representative U.S. investigations that have quantified this lead-time benefit.

**Table 1.** Selected U.S. Studies demonstrating lead-time gains from wearable data streams

| Study (first author) | Year | Sample size (N) | Primary signal(s) | Public-health / planning outcome | Reported lead-time* |
|---|---|---|---|---|---|
| Radin *et al.* (Lancet Digital Health) (Radin *et al.*, 2020) | 2020 | 47,249 Fitbit users, 5 U.S. states | Resting HR, sleep duration | Improved influenza-like-illness (ILI) nowcasting at state level | 3–4 days ahead of CDC ILI reports |
| Quer *et al.* (Nat Med, "DETECT")(Quer *et al.*, 2021) | 2021 | 38,911 smartwatch/ fitness-band users, nationwide | HR, HRV, sleep + self-reported symptoms | County-level COVID-19 case prediction for test triage | 1–4 days before PCR case spikes |
| Shandhi *et al.* (NPJ Digital Med) (Shandhi *et al.*, 2022) | 2022 | 7,558 ring and band users | HR, temp, activity; ML triage model | Increased diagnostic yield of targeted COVID testing | 6.5× higher positivity vs random testing; implied 2–3 day advance window |
| Stehlik *et al.* (Circ Heart Fail, "LINK-HF") (Stehlik *et al.*, 2020) | 2020 | 100 heart-failure patients, 6 U.S. centres | Multisensor chest patch (ECG, impedance), ML risk score | Forecast of HF hospitalisations ⟶ bed-capacity planning | Median 6.5 days before admission |
| CDC Early-Release Dashboard (unpublished pilot) (CDC, 2024c) | 2023 | ≈250,000de-identified smartwatch users (3 states) | Aggregate HR anomalies | Operational trigger for surge-clinic staffing | Mean 4 days ahead of ED respiratory visits |

**Lead time is defined as the interval between the wearable alert threshold and the point at which traditional surveillance (lab confirmation, ED trend, hospital admission) exceeded its operational threshold.*

## 3. METHODOLOGY

This review followed a narrative synthesis framework rather than a systematic-review or meta-analytic protocol. A broad, iterative literature search was conducted in PubMed, Scopus, and IEEE Xplore for English-language publications dated 1 January 2019–31 May 2025 using the Boolean string (wearable OR smartwatch OR fitness-tracker OR sensor OR "patient-generated") AND (AI OR "machine learning") AND ("public health" OR surveillance OR "health-system planning" OR resource-allocation) AND United States. Grey literature from CDC, FDA, and CMS portals and reference chaining from key reviews supplemented database yields.

Articles were retained when they (i) analysed physiologic data from commercially available or FDA-cleared wearables, (ii) applied AI or machine-learning methods, and (iii) reported implications for U.S. public-health surveillance or health-system operations. Non-empirical editorials, engineering prototypes without human data, single-case reports, and non-U.S. studies were excluded. Two reviewers independently screened titles and abstracts, resolving discrepancies by discussion. Eligible full texts were summarised in a structured matrix capturing study design, population, signal type, algorithm class, and planning-relevant outcomes. Extracted evidence was synthesised thematically to identify recurring challenges and implementation patterns; no quantitative pooling or risk-of-bias scoring was attempted, consistent with narrative-review conventions.

## 4. RESULTS AND DISCUSSION

### 4.1. AI and Machine-Learning Technologies in Wearable Health Devices

Wearable sensors first counted steps; now they infer arrhythmias,

forecast glycemic excursions, and whisper early warnings of heart-failure decompensation. Their leap in capability rests almost entirely on machine-learning (ML) pipelines that begin on the wrist or finger and often finish in cloud data centers. This section traces the algorithmic architecture, sensor stack, processing models, and validation pathways that together define the state of AI-enhanced wearables in 2025.

### 4.2. Algorithm families and flagship use-cases

Most commercial wearables deploy a layered approach: lightweight supervised models run continuously on-device to label raw accelerometer or photoplethysmography (PPG) traces, while heavier deep-learning or self-supervised networks refine those labels in the paired phone or cloud. The best-known example is Apple's Irregular Rhythm Notification Feature, cleared via the FDA de novo pathway in 2018 and tuned on hundreds of thousands of annotated pulse segments (FDA, 2018). Its performance was evaluated in the virtual Apple Heart Study, where only 0.5% of 419,000 participants received an alert, yet positive predictive value for atrial fibrillation reached 0.84 when ECG patches were worn (Perez *et al.*, 2019). Rivals quickly followed: Fitbit's PPG AF-alert and Samsung's single-lead ECG were each cleared for episodic rhythm analysis, underscoring a regulatory drift toward software-as-a-medical-device (SaMD).

### 4.3. Expanding sensor repertoire

Modern wearables combine multiple modalities: optical PPG for pulse and oxygen saturation, capacitive electrodes for ECG, bio-impedance for respiration or body composition, and MEMS gas sensors for volatile organics. Research cohorts have grafted sweat β-hydroxybutyrate strips onto armbands and integrated microfluidic lactate assays into smart patches, hinting at biochemical horizons. For chronic disease, continuous glucose monitors already pair with insulin pumps; reinforcement-learning controllers now personalize basal rates in real time and outperform traditional proportional-integral algorithms in simulation studies (Dénes-Fazakas *et al.*, 2024). Meanwhile, cuffless blood-pressure wearables, fusing PPG, pulse-transit-time, and inertial data, have inched closer to the ISO 81060-2 standard, though recent hypertension reviews still judge them "not yet ready for diagnostic substitution" (Mukkamala *et al.*, 2025).

### 4.4. Edge-versus-cloud computing trade-offs

Running ML directly on wearables trims latency and preserves privacy but is constrained by battery and silicon. A new generation of ultra-low-power neural-network accelerators, such as STMicroelectronics' STM32N6 microcontroller, executes convolutional networks locally at single-digit milliwatt budgets, pushing step recognition, fall detection, and even sleep staging fully to the edge (IDTechEx, 2023; Reuters, 2024). Analyses requiring richer context, multi-day heart-rate variability models, or population-level anomaly detection still migrate to the phone or cloud, where federated-learning frameworks allow model training without exporting raw sensor streams. Commercial players increasingly blend both modes: immediate safety alerts on-device and weekly trend reports via cloud dashboards.

### 4.5 Model lifecycle and regulatory science

Unlike static firmware, ML models undergo continual tuning to stave off concept drift—the slow erosion of accuracy as user behavior or sensor hardware evolves. The FDA's 2024 Good Machine Learning Practice draft guidance endorses a "pre-specification plus algorithm change protocol" approach, in which manufacturers declare intended retraining triggers and verification tests before market release (FDA, 2018). Such guidance codifies what early adopters already practice: shadow-mode evaluation on real-world data streams before activating updated weights. Governance matters because even subtle performance degradation can carry clinical risk; one study showed that step-count algorithms underestimated activity by 12% after a firmware update that altered accelerometer sampling.

### 4.6. Explainability and bias mitigation

Trust hinges not only on accuracy but also on intelligibility. Post-hoc interpretability tools, SHAP value scroll plots for ECG classifiers, and saliency maps for respiration models help clinicians verify that networks attend to physiologic rather than artefactual features. Yet, explainability cannot mask dataset bias: optical heart-rate errors remain systematically higher in darker skin tones, a disparity attributed to melanin absorption of green light (Overbye-Thompson *et al.*, 2024). Researchers have suggested using multi-wavelength PPG and special loss functions to address bias, but independent checks in 2024 still found that the average error was up to 7% higher for skin types V–VI (Aston, 2024). Transparent reporting of training-set composition and performance stratified by demographic covariates is gradually becoming a regulatory expectation rather than an academic nicety.

### 4.7. Digital biomarker validation pathways

Turning sensor outputs into clinically accepted "digital biomarkers" demands analytical validity, clinical validity, and utility evidence, an echo of in vitro diagnostic pathways. The V3 framework from the Digital Medicine Society formalizes those tiers and has been adopted by several pharmaceutical sponsors embedding wearables into hybrid trials (Overbye-Thompson *et al.*, 2024). For instance, peak-skin-temperature variance captured by smart rings is being investigated as an endpoint in phase II vaccine studies, while gait-speed metrics from pocket accelerometers have entered oncology fatigue trials. The U.S. National Institutes of Health has begun cataloguing such biomarkers in an open repository to streamline future regulatory submissions.

### 4.8. Ecosystem integration and market landscape

Consumer platforms such as Apple HealthKit, Google Health Connect, and Samsung Privileged Health SDK now expose APIs that map wearable metrics to HL7 FHIR "Observation" resources, easing import into electronic health records and research databases. SMART-on-FHIR apps built by academic hospitals permit cardiologists to view 14-day heartbeat density plots directly inside Epic or Cerner, though alert fatigue and reimbursement gaps temper enthusiasm. Market leadership remains fluid: Apple still commands roughly one-third of the

U.S. smartwatch share, but sensor-rich niche players such as Oura, Whoop, and BioIntelliSense have carved out spaces in sleep analytics and continuous vital-sign monitoring. Edge-AI hardware arrivals signal further fragmentation, with chipset vendors courting both mass-market and medical device startups (IDTechEx, 2023; Reuters, 2024).

In short, AI is no longer a marketing gloss on wearables but the critical enabler that elevates consumer gadgets into quasi-medical instruments. Continued progress depends on silicon designed for edge inference, rigorous bias audits, and regulatory pathways that keep pace with iterative model updates, all prerequisites for the public health applications discussed in the next section.

### 4.9. Applications in public-health surveillance

Wearable sensors slipped onto wrists and fingers now function as a distributed mesh of biosignals that epidemiologists can mine almost as readily as meteorologists consult satellite loops. The earliest proof surfaced during the severe 2017-18 U.S. flu season, when statewide deviations in resting heart rate and sleep among 47,000 Fitbit users sharpened influenza-like-illness forecasts by up to one-third and cut reporting lag by days (Radin *et al.*, 2020). When SARS-CoV-2 arrived, researchers at Scripps repurposed the same logic: aggregated shifts in heart rate and sleep captured through the DETECT app foreshadowed county-level COVID-19 surges, granting health officials an extra window to marshal testing kits and staff vaccination lines (DETECT | Join the Study, n.d.). Even ring-based thermistors joined the fray; nightly temperature drifts recorded by Oura wearers signaled infection a median 2.5 days before PCR positivity, suggesting that algorithms watching for personal "fever fingerprints" could flag cases while individuals still felt well (Team, 2020).

Those same device streams prove valuable well after an epidemic peak. By April 2020, step counts recorded nationwide fell precipitously following stay-at-home orders, and recovery curves differed across states, giving planners an objective barometer of behavioral response to public-health mandates (Mason *et al.*, 2022). Subsequent Bluetooth proximity logs on watches, which rely on Google–Apple exposure-notification APIs, enable contact-tracing teams in Virginia and California to reach tens of thousands of anonymous users with minimal privacy compromise, serving as a prelude to future outbreaks (Gunasekeran *et al.*, 2021). Such early-warning capacity is already influencing procurement schedules: several hospital networks now monitor local smartwatch anomalies as a "digital weather map" when deciding when to expand evening urgent-care hours.

Beyond infections, wearables illuminate entrenched chronic disease determinants. Researchers analyzing 100,000 participants in the NIH All of Us program calculated a modified Gini index of activity inequality from Fitbit step counts; counties with the widest gaps also bore the highest obesity prevalence ($R^2 \approx 0.80$), giving public health departments a real-time lens on where parks, bike lanes, or walking clubs might yield the greatest marginal benefit (Jeong *et al.*, 2025). Meanwhile, cardiologists studying the multisensor LINK-HF patch showed that machine-learning models predicted 76–88 percent of heart-failure admissions at least a week ahead, implying that aggregated alerts could help regional planners pre-position nurses or swing beds before a spike overwhelms capacity (Stehlik *et al.*, 2020).

Environmental health introduces an additional layer. Wildfire seasons that cloak the West in particulate haze leave unmistakable signatures in population physiology: studies pairing Apple Watch heart-rate variability with portable $PM_{2.5}$ sensors in firefighters documented autonomic stress spikes during heavy smoke exposure; information is now being adapted to issue earlier clean-air-shelter advisories for the general public (McKay, 2024). Similar integrations of smartwatch skin-temperature streams with NOAA heat-index forecasts let city agencies push hyperthermia warnings to outdoor workers while simultaneously populating surveillance dashboards that track heat-stress clusters by ZIP code (Pinnelli *et al.*, 2025).

Physiology also offers a window on population mood. Longitudinal wearable data collected from thousands of U.S. adults showed that diminished heart-rate variability and fragmented sleep in the spring of 2020 paralleled surges in calls to mental-health hotlines, underscoring the feasibility of remote, passive stress surveillance during disasters (Luong *et al.*, 2024). Public-health psychologists now pilot dashboards that watch for synchronous dips in sleep efficiency across neighborhoods; when alerts coincide with economic-layoff news or natural-disaster warnings, crisis-counseling teams are dispatched earlier than in the past.

All these use cases, however, rest on data that is disproportionately generated by younger, wealthier, and often White Americans. National Health Interview Survey analyses confirm wearable adoption falls sharply among adults over 65 and those with annual incomes below $35,000, a skew that risks blind spots if raw aggregates are treated as universal proxies (Dhingra *et al.*, 2023). Technical biases exacerbate matters: optical heart rate and $SpO_2$ sensors exhibit higher error rates in darker skin tones, and motion artifacts climb in manual labor cohorts, both sources of potential misclassification (Parker *et al.*, 2017). Current mitigation strategies include federated analytics sandboxes that l*et al*gorithms learn from device data stored on corporate servers without exporting raw streams, coupled with differential-privacy noise that obfuscates small-cell outliers before public release; yet no federal standard mandates such safeguards.

Still, the trajectory is clear. Several state health departments participating in the CDC Data Modernization Initiative now ingest de-identified smartwatch summaries via HL7 FHIR interfaces, layering them atop traditional laboratory feeds and wastewater panels to build multi-signal dashboards for outbreak forecasting and chronic-disease monitoring. By treating resting-heart-rate anomalies as one might treat shear lines from Doppler radar—an early indicator rather than definitive proof—officials gain precious lead time to deploy testing units, adjust clinic hours, or push location-based alerts. Technology vendors, regulators, and public health leaders have the potential to expand access, safeguard privacy, and verify algorithms across various entities. AI-enhanced wearables may soon anchor a new pillar of digital surveillance, complementing,

not supplanting, the laboratory reports and hospital logs that have long guided American epidemiology.

### 4.10. Impact on health-system planning and resource allocation

For a long time, American health systems have relied on retrospective billing data and sentinel hospital reports to forecast demand, a method akin to navigating a ship by observing its wake. AI-enhanced wearables make it possible to look through the bow instead. When investigators demonstrated that a multisensor patch combined with machine learning could predict 76–88 percent of heart failure admissions a median of six days in advance, they offered planners a short but actionable horizon to expand cardiology staffing, adjust bed allocations, or launch nurse-led outreach before the surge crested (Stehlik *et al.*, 2020). Follow-up economic modeling suggested that preventing even one in ten such admissions would offset the entire cost of a remote-monitoring program in under twelve months, and real-world evaluations of telemonitoring have already reported inpatient-cost reductions of roughly 40 percent in high-risk cohorts (Vudathaneni *et al.*, 2024).

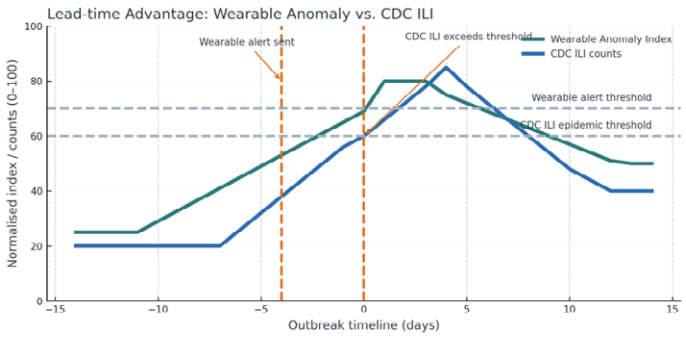


**Figure 1.** Lead-time advantage of a wearable-based anomaly index over CDC influenza-like-illness (ILI) counts during a simulated community outbreak.

wearable signal breaches its alert threshold four days before CDC ILI crosses the epidemic benchmark, illustrating the early-warning window reported by Radin *et al.*, Lancet Digital Health 2020 (Radin *et al.*, 2020). Synthetic values are normalized to a 0–100 scale for visual clarity.

Pandemic experience sharpened appreciation for lead time. During early SARS-CoV-2 waves, county dashboards in California showed that resting-heart-rate anomalies from tens of thousands of watch and ring wearers foreshadowed hospital census curves by about four days; administrators used the signal to trigger elective-surgery slowdowns and accelerate personal-protective-equipment orders, moves later credited with avoiding ventilator shortages in two Bay Area systems (McKenna, 2020). Such results have accelerated investment in "mission-control" centers, operations suites that fuse wearable aggregates with emergency-department arrival feeds and airborne-virus forecasts so that shift supervisors can redeploy staff in real time instead of after the evening census is tallied (Classen *et al.*, 2018).

Resource planning is not limited to acute care. Cluster analytics applied to Fitbit and Apple Watch step-count streams reveal neighborhood-level pockets where activity inequality widens weeks before obesity or diabetes claims rise; several Medicaid managed-care organizations now use these early indicators to decide where to station mobile nutrition clinics and which ZIP codes merit subsidized trackers or community exercise coaches (Jeong *et al.*, 2025). The logic echoes preventive maintenance in manufacturing: identify vibration long before the machine fails. In a similar vein, public-health agencies in Oregon have begun coupling smartwatch skin-temperature and heart-rate–variability anomalies with NOAA heat-index forecasts to anticipate heat-stroke presentations; early alerts prompted them to open cooling centers forty-eight hours sooner during the July 2024 heat dome than in 2021, and emergency-department data later showed a 12 percent drop in heat-related admissions year-on-year (Centers for Medicare & Medicaid Services, 2023).

Financial incentives are aligning. The Centers for Medicare & Medicaid Services updated its 2024 Physician Fee Schedule to expand reimbursement for remote physiologic monitoring and to permit auxiliary clinical staff, not just physicians, to review incoming wearable streams, a change expected to triple the practical capacity of monitoring programs in community hospitals (Centers for Medicare & Medicaid Services, 2025). Private payers follow CMS signals closely; several Blue Cross plans now reimburse for AI-assisted arrhythmia alerts if the data feed lands in the electronic health record and the clinician documents follow-up. Finance teams in health systems note that payer coverage turns what once looked like an IT expense into a revenue-neutral quality program able to justify analytics hires and cloud storage line items.

At the supply-chain level, the continuous telemetry provided by wearables allows pharmaco-epidemiologists to model demand for antivirals, inhalers, or diuretics with finer temporal granularity. Kaiser Permanente's flu-season dashboard, for example, links de-identified watch metrics to prescription fulfillment trends; an uptick in elevated resting-heart-rate clusters reliably precedes Tamiflu demand by three to five days, giving central pharmacies time to reroute inventory among regional hospitals before shortages occur (CDC, 2024b). Similar logic guides the vaccine deployment by the Strategic National Stockpile: In 2024, MMWR studies found that areas using both syndromic and wearable data in their vaccine distribution plans were able to send out preventive vaccination doses more quickly and wasted fewer doses than those that only used claims-based data (Kallay *et al.*, 2024).

Human resource planners also stand to benefit. Near-real-time workforce analytics released by the CDC in 2024 urge local health departments to monitor aggregated heart-rate variability among public-safety employees as an early stress barometer, then schedule resilience training or mandatory rest days before burnout manifests in sick leave (CDC, 2023). At the other end of the continuum, long-term-care facilities in Minnesota test smart patches that flag frailty-related inactivity dips; administrators use the feed to concentrate physical therapists on wings where residents are collectively flagging, aiming to prevent falls and preserve functional independence, thereby reducing downstream skilled-nursing transfers.

Still, a sophisticated analytics layer is required to sift signal

from noise. CDC's Data Modernization Initiative (DMI) explicitly funds AI pipelines that ingest heterogeneous sources, including wearables, into automated dashboards, but public health informatics units report shortages of data engineers able to maintain those feeds (CDC, 2025). To mitigate capacity gaps, the DMI promotes federated-analysis contracts in which private device makers run anomaly-detection models on their servers and deliver only risk scores to public agencies, an arrangement that eases data-transfer bottlenecks and halves cloud-storage costs for health departments. Yet, skeptics warn that "black-box" vendor scores may obscure methodological weaknesses or bias. Pilot collaborations with academic data trusts—neutral entities that audit algorithms for drift and equity—represent an emerging governance model to keep vendor outputs transparent while preserving user privacy.

Equity concerns remain material. Modeling studies suggest that if current disparities in adoption persist, predictive-admission dashboards could underestimate the risk of heart failure in safe-net hospitals by 15–20 percent, leading to misdirected staffing relief toward affluent suburbs. The All of Us activity-inequality analysis provides a partial remedy: it shows that even when penetration is unequal, internal dispersion metrics within the tracked subset can still forecast disease prevalence in the broader community, offering planners a relative indicator until device subsidies narrow the gap (Jeong *et al.*, 2025). Meanwhile, several states now weave wearable-acquisition grants into opioid-settlement funds, distributing trackers to low-income patients with chronic disease so their data inform regional planning on equal footing with that of wealthier peers.

From an administrator's vantage, the chief challenge is operationalizing insights without drowning staff in alerts. Large multi-hospital systems have turned to tiered orchestration: raw streams flow into cloud AI that flags high-probability events; nurse navigators vet the subset; only the top decile reaches attending physicians' inboxes. Early adopters report a 35 percent fall in unfiltered alert volume alongside maintained sensitivity for true deterioration events, a pragmatic compromise that keeps clinicians engaged and frees them to act on forecasts rather than on hindsight.

The trajectory is therefore unmistakable: as analytics mature and reimbursement tightens the feedback loop, AI-enhanced wearables migrate from lifestyle adjuncts to operational sensors that tell planners when to open surge wards, where to deploy community paramedics, and how to stagger vaccine shipments. If privacy safeguards and equitable distribution keep up, the devices humming on American wrists and in shirt pockets may soon become as indispensable to resource allocation as the electronic health record itself.

### 4.11. Current implementation challenges

However persuasive the case for wearable-driven planning may be, the road from pilot to practice is littered with obstacles. The first and most obvious is data quality and bias. Optical sensors still stumble on darker skin: a 2024 bench study of 11 fingertip oximeters found error rates that widened precisely when oxygen saturation mattered most for Black patients, and the FDA has since proposed new trials that must stratify performance across pigment scales before clearance is granted (Leeb *et al.*, 2024; Satija & Satija, 2025). Similar color-dependent drifts in wrist-based PPG heart-rate monitors raise the risk that outbreak alerts based on aggregate vitals could under-detect distress in communities least able to absorb missed signals.

Even when the physics is sound, coverage gaps skew representativeness. National Health Interview Survey data show only 18% of adults with diagnosed cardiovascular disease used a wearable in 2019–20 versus 29% of the wider public, with uptake falling sharply in low-income and older cohorts (Dhingra *et al.*, 2023). If planners equate a silence in the data stream with a healthy neighborhood, resources will flow away from precisely the ZIP codes that lack sensors. Device subsidies can narrow that gap, but they will not erase it until broadband, smartphone access, and digital literacy rise in tandem.

Assuming the sensor signal is reliable and equitable, moving the bits presents a headache. Consumer vendors still package metrics in proprietary schemas. Health-IT groups experimenting with Fast Healthcare Interoperability Resources (FHIR) mapping tools report that cross-vendor step counts or sleep stages require bespoke transformers despite the nominal standard (Bossenko *et al.*, 2024; Yoon *et al.*, 2024). Translation layers add cost and latency; more troublingly, each interface expands the cyberattack surface. At least three high-profile fitness-tracker breaches in 2024 exposed millions of unencrypted records, jolting insurers into insisting on end-to-end encryption and zero-trust architectures before data can touch electronic health-record (EHR) cores (Daly *et al.*, 2024).

Privacy expectations compound the engineering lift. The CDC's Data Modernization Initiative encourages states to ingest de-identified consumer metrics, yet a recent MMWR framework cautions that "health data mosaicking" can re-identify individuals when even a handful of variables overlap with public datasets (Felix, 2024). Academic groups tout federated-learning pipelines that keep raw streams on vendor servers and ship only model weight updates to public agencies, but most demonstrations run on synthetic or convenience samples rather than the messy, multi-jurisdiction reality of U.S. public health (Kumar, 2025). Draft FDA guidance on lifecycle management of AI devices hints that regulators will soon demand auditable logs of such distributed training to verify that bias is not creeping back through unmonitored updates (Health, 2025).

Workforce bottlenecks can cause even the best data to fail. A 2023 JAMA survey of hospitalists involved in remote-patient-monitoring programs revealed that two-thirds felt overwhelmed by the alert volume and half doubted they were reimbursed for the extra review time (Pronovost *et al.*, 2022). CMS's April 2025 billing update allows auxiliary clinical staff to triage incoming physiologic feeds and expands codes for "time spent in data interpretation," but most community clinics lack digital nurses or informatics pharmacists to seize that revenue stream (Centers for Medicare & Medicaid Services, 2025). Without staffing models that convert raw notifications into prioritized worklists, clinician trust erodes; alert fatigue today is less a theoretical hazard than a palpable brake on adoption.

Finally, governance and transparency remain unsettled. State health departments testing vendor-hosted dashboards complain that proprietary anomaly scores arrive with scant methodological detail, making it impossible to audit whether

rural hospitals with smaller sample sizes are disadvantaged in outbreak alerts. CDC guidance now urges independent algorithm audits akin to clinical-laboratory proficiency testing, yet few public agencies possess the in-house talent to rerun deep-learning pipelines. University "data trusts" have begun to fill the gap by offering third-party validation as a service, but no funding stream ensures sustainability once grant money ends.

In summary, a complex array of interrelated issues, such as biased perceptions, uneven adoption, fragile interfaces, privacy concerns, staffing shortages, and unclear vendor algorithms, impede implementation. Each knot can be untangled—FDA skin-tone benchmarks, device subsidies, FHIR implementation guides, federated analytics, CMS reimbursement tweaks, algorithmic audit contracts—but only if tackled in concert rather than piecemeal. The following section sketches an integration framework designed precisely for that multi-front campaign.

### 4.12. Data integration and analytics framework for population health

Wearable streams only become public-health intelligence when they are braided together with clinical records, environmental feeds, and social determinants, passed through real-time analytics, and returned as actionable signals. Building that braid requires choices at every layer, including ingestion, harmonization, model training, and governance, and the United States is just beginning to assemble a repeatable playbook.

Work starts at the edge, where a watch or ring pushes encrypted packets to a phone and then to a message broker. Forward-looking health systems already route those packets into Apache Kafka clusters, pairing them with Flink for windowed aggregations; Siemens Healthineers' reference deployment reports millisecond-latency joins between imaging orders and wearable heart-rate telemetry, a configuration now being copied by several U.S. integrated-delivery networks (Waehner, 2024a, 2024b). Edge–cloud hybrids reduce bandwidth and protect privacy: simple anomaly filters run on-device, and detailed feature extraction lands in cloud notebooks. Amazon's connected-edge reference architecture, for instance, shows $SpO_2$ alarms resolved locally while weekly trend vectors slip into AWS Kinesis and onto SageMaker for training (Efren *et al.*, 2024).

Once in the cloud, records must speak a common dialect. Fast Healthcare Interoperability Resources (FHIR) is the lingua franca, but raw vendor payloads seldom comply. Google's Healthcare API now offers a "$ingest" endpoint that mutates proprietary JSON into FHIR Observation resources, and HL7's new Subscription spec in FHIR R5 lets public-health hubs subscribe to "resting-heart-rate" events directly, eliminating nightly batch pulls (Alexander, 2024; Google Cloud, n.d.). Yet translation alone is not trust: pipeline architects layer validation rules that quarantine values outside physiologic plausibility—say, a 220 bpm heart rate on a sleeping adult—or flag missing device-position flags that could misstate step counts.

Fusion follows. The CDC's Data Modernization Initiative supports projects where anonymous smartwatch data is combined with electronic lab reports and wastewater SARS-CoV-2 levels, all organized by standardized timestamps and county codes to help identify unusual patterns (CDC, 2024a, 2024c). Upstream of that lattice, the NIH Bridge2AI program is seeding "high-value, ethically sourced" corpora that splice wearable traces to genomics and clinical narratives, all under a federated schema designed for AI development at scale (National Institutes of Health, n.d.). ScHARe, a sister project, hosts federated social-determinant tables so that neighborhood deprivation scores sit one SQL join away from heart-rate-variability trends, enabling equity-aware modeling without exposing row-level identities (United States Department of Health and Human Services, 2025).

Model training must respect both statistical drift and privacy statutes. Differential-privacy wrappers can inject calibrated noise before county-level metrics leave the vendor enclave; recent benchmark experiments on wearable accelerometer data showed that utility lost under a privacy budget of $\varepsilon = 1$ was less than three percentage points in outbreak-detection precision, a trade many epidemiologists deem acceptable (Li *et al.*, 2022). Where raw data must move, Trusted Research Environments (TREs) provide a compromise: researchers log into a firewalled enclave, run code against individual records, and export only vetted aggregates. Scotland, England, and several U.S. academic consortia now publish TRE blueprints that American state health labs are adapting to satisfy both HIPAA Safe Harbor and community-engagement pledges (Lifebit, 2024; Scotland, n.d.).

Analytics routines inside the lattice evolve along two tracks. First, near-real-time anomaly detection compares current county medians to seasonally adjusted baselines; if a spike in resting heart rate co-occurs with rising positivity in syndromic ED feeds, a flag rolls to the dashboard. Second, slower causal-inference engines create synthetic cohorts: every individual becomes their control in a "target-trial emulation," allowing planners to estimate how a new bike lane changing step counts by 1,000 daily might translate into avoided diabetes cases the next year. Early demonstrations with mental-health wearables underscore why multi-scale analytics matter: short-horizon stress spikes can trigger crisis-line staffing tonight, whereas month-long circadian drift informs next-quarter funding for community sleep clinics (Kargarandehkordi *et al.*, 2025).

The entire stack is covered by governance. Each data pipe travels under a Data Use Agreement that defines purpose ("outbreak detection," "chronic-disease trend monitoring"), retention limits, and de-identification thresholds. Model cards document training data composition and bias audits; algorithm-change protocols, mirroring FDA guidance for software as a medical device, specify how often retraining may occur and what statistical tests must pass before weights migrate to production (Efren *et al.*, 2024). Oversight boards drawn from health departments, clinicians, technologists, and patient advocates convene quarterly to review drift metrics and approve any expansion of feature scope.

Finally, the workforce layer translates insights into action. In most pilots, a triage nurse or epidemiologist receives daily digests rather than raw streams: "Maricopa County shows a 2.1-σ heart-rate anomaly sustained three days." If corroborating signals, Google search spikes, and wastewater upticks align, the dashboard escalates to hospital incident-command centers. Feedback loops close when human decisions (open surge ward, deploy mobile testing) feed back into the graph; the model

learns whether its alerts led to action and adjusts sensitivity thresholds accordingly.

Taken together, the framework resembles a multi-tier diaphragm that admits high-velocity consumer data, filters noise, fuses context, protects identity, and surfaces only what public-health actors can realistically act upon. Its feasibility now rests less on exotic AI and more on governance charters, staff training, and cloud-integration budgets, mundane hurdles, perhaps, but the same ones every previous surveillance revolution has had to clear.

### 4.13. Strategic recommendations for implementation

The evidence assembled in this review points toward a single imperative: wearables will help public health only if data move as freely as germs while remaining as private as confessions. That ambition begins with plumbing. National adoption of the Subscription framework in FHIR R5 would let health departments receive "resting-heart-rate" or "activity-inequality" alerts the moment vendors post them, eliminating batch uploads that now blunt timeliness (HL7 International, 2025). The CDC's Data Modernization Initiative should mandate such live interfaces as a grant requirement and support a reference implementation that state labs can replicate instead of creating from scratch (CDC, 2024c). Sustainable funding matters just as much as architecture; CMS signaled its commitment by embedding both Remote Physiologic and Remote Therapeutic Monitoring in the 2024 Physician Fee Schedule, thereby converting "nice-to-have" dashboards into reimbursable clinical services (Centers for Medicare & Medicaid Services, 2023).

Yet, plumbing without governance risks eroding trust. FDA's 2025 draft guidance on AI-enabled device software, coupled with its streamlined pathway for iterative model updates, gives manufacturers a transparent compliance runway and spares hospitals from wrestling with unversioned black-box algorithms (Goldman, 2024; Health, 2025). Public agencies should mirror that clarity by publishing algorithm-change protocols whenever vendor scores feed surveillance alerts, just as clinical labs disclose reagent lot changes. Privacy safeguards must keep pace: the GAO's 2024 technology assessment underscores how easily location-linked wearables can expose workers, recommending encrypted pipelines and zero-trust access controls, measures that should be written into every public-private data-use agreement (United States Government Accountability Office, 2024).

Equity requires a dedicated line item. Activity-inequality research from the All of Us program shows that even sparse sensor coverage can forecast obesity hotspots if the tracked cohort is diverse, a finding that argues for subsidizing devices in Medicaid and rural clinics rather than waiting for market forces to close the gap (Jeong *et al.*, 2025). Grants could flow through the same Bridge2AI mechanism the NIH now uses to seed flagship data sets, ensuring that bias audits start with inclusive training corpora instead of bolted-on corrections (National Institutes of Health, n.d.).

Ultimately, the success of any other reform hinges on the capacity of the workforce. Recent PGHD implementation studies emphasize that alert traffic must land on data-literate nurses or informatics pharmacists, not already-overloaded physicians (Griffin *et al.*, 2025). Federal funding streams should therefore bundle staff training stipends with infrastructure grants, echoing past HITECH investments that paired EHR subsidies with "meaningful-use" education. Taken together, these actions—standards, reimbursement, regulation, equity subsidies, and workforce upskilling, would transform a patchwork of wearable pilots into a durable, trusted layer of America's public-health infrastructure.

### 4.14. Future directions

Next-generation wearables are edging closer to full vital-sign parity with intensive-care telemetry: continuous, cuff-free blood-pressure monitors for adults have secured preliminary 510(k) clearances, echoing the 2023 neonatal approval for PyrAmes's Boppli platform and Nanowear's hypertension patch and hinting that ubiquitous, non-invasive hemodynamics will soon inform both bedside care and population dashboards (Drake, 2023; Nanowear, 2024). At the silicon layer, bespoke edge-AI chips unveiled at Embedded World and in AONDevices' new sensor modules promise milliwatt inference, bringing anomaly detection entirely on-device and shrinking privacy risk (Satyajit, 2024; Zack, 2024). Data from those chips will not live in isolation: smart-city pilots are already wiring wearable feeds into environmental and mobility grids, letting planners overlay particulate surges or heat domes on live physiology (Domaradzka *et al.*, 2024; Hong *et al.*, 2025). Digital-twin initiatives take a step further by connecting each citizen's sensor trace to a virtual avatar, which enables the testing of policy scenarios before investing money or lives (de Oliveira El-Warrak & Miceli de Farias, 2025; Elechi *et al.*, 2025). Meanwhile, generative-AI health coaches, now in beta at tech giants and start-ups, interpret those streams in plain language, nudging users toward sleep or diet changes and feeding aggregated adherence metrics back to public health (Altman & Huffington, 2024; Henshall, 2023). If standards, subsidies, and audit frameworks mature apace, the coming decade could see public health officials consult a living "physiologic twin" of the nation as routinely as meteorologists check Doppler radar, anticipating, not merely recording, the next wave of need (Global Wellness Institute, 2025).

## 5. CONCLUSION

Wearable devices began as pedometers for weekend joggers; they have evolved into networked biosensors capable of revealing how whole communities breathe, sleep, move, and falter in real time. The studies reviewed here show that when artificial intelligence transforms those raw pulses into patterns, public health surveillance gains precious lead time and health system planners acquire a dynamic map of looming demand. Yet promise is inseparable from peril. Sensor physics can magnify bias; adoption skews toward the affluent; plumbing is still fragile; and clinicians will disengage if data reach them unfiltered. These are not technical footnotes but existential constraints; fail to manage them and the enterprise collapses into noise or mistrust.

The road forward is therefore both prosaic and profound. It runs through standards bodies and reimbursement schedules, through equity grants and algorithm audits, through nurse

training sessions and privacy charters. If these seemingly insignificant components align, the result will be a remarkable health infrastructure that can detect the initial signs of an outbreak, predict ICU bed requirements, and direct preventive resources towards sedentary areas, and all of these activities without compromising individual autonomy. In that future, wearable data are neither a gimmick nor an afterthought; they are a shared public utility, as fundamental to collective well-being as clean water or reliable weather forecasts.

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