Low-Latency Biometric Synchronization for Digital Health Applications: A Layered Service Architecture for Multi-Device Time Alignment, Streaming, and Record Reconciliation

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Abstract

Digital health applications increasingly consume biometric signals from several sources at once: a wrist wearable, a chest sensor, a phone's own sensors, and companion devices, feeding visualizations, alerts, and interventions that are only as sound as the temporal relationships among the streams. Synchronization in this setting is a stack of related but distinct problems, clock alignment across devices without shared time infrastructure, stream alignment so that samples from different sensors can be fused at analysis time, delivery with bounded latency to local and remote consumers, and state reconciliation so that intermittently connected devices converge on one record, and digital health engineering routinely solves each ad hoc, if at all. This paper develops a research concept for a low-latency biometric synchronization layer for digital health applications, specified as four cooperating services with explicit contracts. A time alignment service maintains per-device clock models against the phone's reference using offset-and-drift estimation over exchange protocols adapted from sensor network synchronization, stamping every sample with reference-time bounds. A stream alignment service performs windowed, uncertainty-aware resampling and fusion gating, so that multi-signal features are computed only when alignment error is within declared tolerance. A delivery service streams aligned samples and derived events over persistent full-duplex channels with sequence numbering, typed backpressure, and snapshot-plus-delta resumption. A reconciliation service treats the health record as a replicated dataset with conflict-free merge semantics, guaranteeing convergence across offline periods without data loss. A phased evaluation plan measures achievable alignment error across device classes, end-to-end latency decomposition, convergence behavior under partition, and the downstream effect of alignment quality on representative multi-sensor computations. Applications, limitations, and privacy obligations are analyzed.

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1. Introduction

The clinical and behavioral promise of mobile health rests on continuous measurement, and the field's foundational assessments made the case while flagging the evidentiary and engineering gaps between sensing and health value (Free *et al*., 2013; Kumar *et al*., 2013; Steinhubl *et al*., 2015) [45, 62, 112]. Programmatic work on scaling mobile health for chronic disease monitoring and adherence support has since confirmed that the binding constraints are organizational and infrastructural rather than sensory (Oparah, Gado, *et al*., 2021) [87], a pattern equally visible in the telehealth literature on bridging rural and urban access disparities (Oparah, Gado, *et al*., 2024b) [88] and in reviews of trust, privacy, and regulatory governance in AI-powered remote monitoring (Akintola *et al*., 2025) [14]. A decade of consumer and clinical wearables has since made multi-sensor bodies ordinary, wrist photoplethysmography, chest electrocardiography, inertial sensing, and phone-resident signals coexisting on one person (Piwek *et al*., 2016; Patel *et al*., 2012; Pantelopoulos & Bourbakis, 2010; Majumder *et al*., 2017) [101, 99, 98, 66], joined by biometric and Internet-of-Things capture devices whose deployment patterns are now routine in non-clinical settings as well (Ussher-Eke *et al*., 2025) [116], and the digital biomarker agenda now asks these signals to support decisions, which imposes measurement discipline on the whole chain from sensor to record (Coravos *et al*., 2019; Afrihyia, Akinse, & Ojukwu, 2023; Ilodigwe & Adesemoye, 2026b) [37, 4, 54].

Temporal structure is where that discipline is most often silently violated. Physiological computation is timing-sensitive at scales devices do not respect by default: beat-interval analytics presuppose millisecond-accurate event times (Task Force, 1996; Pan & Tompkins, 1985) [114, 97], pulse arrival measurements fuse cardiac and peripheral signals whose relative timing carries the information (Allen, 2007; Elgendi, 2012; Schäfer & Vagedes, 2013) [18, 41, 107], respiration estimation fuses modulations across signals (Charlton *et al*., 2018) [36], and motion artifact handling aligns optical and inertial streams (Zhang *et al*., 2015; Bent *et al*., 2020) [117, 33]. The clinical value of such derived measures is well established, with composite cardiometabolic indices and echocardiographic parameters used together for risk stratification in exactly the populations mobile monitoring targets (Okwah, 2022; Amadi *et al*., 2025) [82, 19]. Yet consumer devices keep independent clocks with drift, deliver samples over links with variable buffering, and reconnect after arbitrary gaps, so the streams arriving at an application are misaligned in ways the application rarely models. The body and multi-sensor fusion literatures identify synchronization as a standing prerequisite of fusion quality (Gravina *et al*., 2017; King *et al*., 2017; Khaleghi *et al*., 2013) [49, 58, 57], and the sensor network field solved clock synchronization rigorously for its own setting long ago, with reference-broadcast, pairwise-exchange, and flooding protocols achieving tight bounds under radio constraints (Elson *et al*., 2002; Ganeriwal *et al*., 2003; Maróti *et al*., 2004) [42, 46, 68], surveyed thoroughly (Sivrikaya & Yener, 2004; Sundararaman *et al*., 2005) [111, 113], atop the internet-scale foundations of clock discipline (Mills, 1991) [71], whose operational exposure as a network service is itself a studied security surface (Jimoh & Ahmed, 2024) [56], and the logical-ordering fundamentals beneath all of it (Lamport, 1978) [63]. What has not been specified is the transfer: a synchronization layer for the phone-centered, intermittently connected, privacy-constrained topology of digital health.

Latency and consistency complete the problem. Health applications increasingly act in the moment, biofeedback, alerts, just-in-time interventions (Nahum-Shani *et al*., 2018) [72], which sets delivery budgets that polling architectures cannot meet and persistent full-duplex channels can (Fette & Melnikov, 2011; Pimentel & Nickerson, 2012; Grigorik, 2013; Loreto & Romano, 2012) [44, 100, 50, 65], while the same devices spend hours offline, which makes the health record a replicated dataset needing principled reconciliation rather than last-write luck, the problem the distributed systems literature answers with convergent replicated types and epidemic reconciliation (Shapiro *et al*., 2011; Terry *et al*., 1995; DeCandia *et al*., 2007; Kleppmann, 2017) [108, 115, 38, 59], and which health systems research frames as a governance and architecture problem for interoperability and data quality at national scale (Ilodigwe & Adesemoye, 2021) [52]. Wireless engineering supplies the complementary framing, since energy, reliability, and latency in constrained radio systems trade against one another rather than improving together (Asiedu & Quainoo, 2024; Quainoo & Ogundapo, 2026b) [26, 102], and on-device intelligence is increasingly the mechanism by which sensitive signals are processed without leaving the handset (Nwakamma *et al*., 2025) [73]. This paper develops the research concept that composes these strands into one specified layer. Section 2 reviews background; Section 3 defines the synchronization stack and requirements; Sections 4 through 7 specify the architecture and its four services; Section 8 sets out the evaluation plan; Sections 9 through 10 treat applications and limitations; Section 11 concludes.

2. Background and Related Work

Clock synchronization research supplies the alignment instruments. Network time discipline established offset estimation over symmetric exchange with drift modeling (Mills, 1991) [71]; sensor network protocols adapted the machinery to constrained radios, removing sender-side nondeterminism via receiver-receiver referencing (Elson *et al*., 2002) [42], bounding pairwise error through timestamp exchange at the media access layer (Ganeriwal *et al*., 2003) [46], and propagating reference time with drift compensation network-wide (Maróti *et al*., 2004) [68], with the survey literature organizing the design space by error sources and topology (Sivrikaya & Yener, 2004; Sundararaman *et al*., 2005) [111, 113]. Precision time protocols standardized high-accuracy distribution where infrastructure permits (IEEE, 2008) [51]. Work on intermittently powered and batteryless networks extends the same problem into the regime where nodes lose power between exchanges, and epoch-aligned reliable broadcast has been proposed precisely to keep such nodes coherent across power gaps (Asiedu & Quainoo, 2025) [27], alongside simulation studies of reliability in large-scale intermittently powered deployments (Asiedu & Quainoo, 2023b) [25] and reviews of radio-frequency harvesting strategies for energy-autonomous sensing (Asiedu & Quainoo, 2023a) [24]. The digital health topology differs from all of these in instructive ways: the phone is a natural reference and gateway, links are consumer radio protocols whose stack timestamping access is limited (Gomez *et al*., 2012) [48], physical-layer impairments and impedance mismatch shape achievable link behavior in ways that propagate into timing variance (Quainoo, Ogundapo, &

Asiedu, 2024) [104], throughput and delay degrade nonlinearly with channel conditions on the Wi-Fi side of the same handset (Quainoo, Ogundapo, & Asiedu, 2025a) [105], devices sleep aggressively for energy (Carroll & Heiser, 2010) [35], and the fleet is heterogeneous and uncontrolled, which together argue for offset-and-drift modeling per device with uncertainty carried explicitly rather than assumed away, the design position Section 5 adopts.

Physiological fusion research defines the tolerance side. Multi-sensor fusion in body networks is a recognized quality chain from alignment through feature fusion to decision fusion (Gravina *et al*., 2017; King *et al*., 2017) [49, 58], within the general fusion taxonomy (Khaleghi *et al*., 2013) [57], and the signal literatures fix concrete tolerances: beat-event analytics at milliseconds (Task Force, 1996; Pan & Tompkins, 1985) [114, 97], cross-signal timing features at similar scales (Allen, 2007; Charlton *et al*., 2018) [18, 36], artifact-gating alignment at sample resolution (Zhang *et al*., 2015) [117]. Downstream, the same signals feed decision support and risk models whose validity inherits every upstream measurement error (Adelanwa, Basnet, & Anene, 2024a; Ilodigwe & Adesemoye, 2024a) [2, 53]. These numbers convert synchronization from an aesthetic into an engineering contract: a fusion computation is valid only when alignment uncertainty is inside its tolerance, which is exactly the gate Section 5's stream service enforces and Section 8's evaluation measures end to end.

Streaming and state synchronization research supplies delivery and convergence. Persistent full-duplex channels are the settled last-hop instrument for low-latency push (Fette & Melnikov, 2011; Pimentel & Nickerson, 2012; Grigorik, 2013) [44, 100, 50], event-time processing gives the semantics for computing over out-of-order streams with watermarks (Akidau *et al*., 2015) [11], durable logs provide the multi-consumer backbone where deployments need it (Kreps *et al*., 2011) [61], and transport evolution toward connection-migrating multiplexed protocols is directly relevant to devices that roam networks (Langley *et al*., 2017; Iyengar & Thomson, 2021) [64, 55]. Applied work on real-time analytics and monitoring pipelines confirms the operational shape of these systems in production settings (Basnet, Oghenemaiga, & Anene, 2023; Orise & Niniola, 2022; Oparah, Ezeh, *et al*., 2023) [31, 89, 86], and portability work on cloud-to-edge execution is relevant to placing the same processing on either side of the boundary (Ojukwu, Oyesiji, & Nwakamma, 2025) [80]. For state, the offline-first problem is classical: replicas that diverge under partition and must converge without loss, addressed by conflict-free replicated data types whose merge functions guarantee convergence (Shapiro *et al*., 2011) [108], by reconciliation systems that made eventual consistency an engineering practice (Terry *et al*., 1995; DeCandia *et al*., 2007) [115, 38], and consolidated for application designers in the data-intensive systems synthesis (Kleppmann, 2017) [59], under the availability-consistency constraints partition imposes (Gilbert & Lynch, 2002; Brewer, 2012) [47, 34]. Health interoperability standards define the record's exit interface, resource-based exchange and app platforms over it (Bender & Sartipi, 2013; Mandel *et al*., 2016) [32, 67], governance and architecture frameworks specify how such records are curated at scale (Ilodigwe & Adesemoye, 2021; Anioke & Atima, 2023c) [52, 21], and the privacy literature defines the governance envelope every layer must respect (Kotz *et al*., 2016; Avancha *et al*., 2012) [60, 30], extended by comparative work on privacy-preserving health data governance (Afrihyia, Ojukwu, & Akinse, 2024) [6], compliant analytics architecture for community healthcare organizations (Aliliele, Mbonu, & Iwuanyanwu, 2024b) [16], ethical data practice in health learning and training systems (Orise & Niniola, 2023, 2025) [90, 92], and cross-jurisdictional harmonization of data protection obligations (Ominyi & Anichukwueze, 2022a; Annan, 2022) [83, 22].

3. The Synchronization Stack and Requirements

The concept defines synchronization as four stacked problems with separable contracts. Clock alignment: maintain, per device, a mapping from device timestamps to reference time with quantified uncertainty, surviving drift, sleep, and reconnection. Stream alignment: place samples from all devices on the reference timeline and expose fusion-ready views whose alignment uncertainty is explicit, so downstream computation can gate on tolerance. Delivery: move aligned samples and derived events to local and remote consumers within budget, with ordering, resumption, and backpressure semantics specified per message type. Record reconciliation: guarantee that the person's health record converges to a single consistent state across all replicas, phone, devices' buffered histories, and service, despite arbitrary offline intervals, with no silent loss and deterministic conflict outcomes.

Requirements bind the stack together. Uncertainty honesty: every timestamp carries bounds, every fused feature carries the alignment error it was computed under, and no layer discards uncertainty it cannot justify, because downstream validity depends on it (Gravina *et al*., 2017; Task Force, 1996) [49, 114], and because performance and outcome measurement systems built on these values inherit whatever error the layer conceals (Adelanwa, Basnet, & Anene, 2024b) [3]. Budget accountability: end-to-end latency decomposes into measured per-layer contributions against application budgets set by the intervention literature's timeliness needs (Nahum-Shani *et al*., 2018) [72], in the manner that service assurance frameworks decompose reliability commitments for systems serving large user populations (Oteri & Edivri, 2026) [95], and against the recognition that latency, reliability, and energy cannot be optimized independently in constrained radio systems (Asiedu, Quainoo, & Asiedu, 2025) [28]. Convergence with provenance: reconciliation outcomes are deterministic, loss-free for observations, and auditable, since the record may feed clinical use (Coravos *et al*., 2019; Mandel *et al*., 2016) [37, 67], with sensitivity classification and traceability mechanisms determining what may be retained and where (Aliliele, Mbonu, & Iwuanyanwu, 2024a) [15] and immutable audit-trail patterns supplying the verification substrate (Oshoba, Hammed, & Odejobi, 2020) [94]. Energy proportionality: alignment traffic and streaming adapt to radio and battery state, respecting the mobile energy hierarchy (Carroll & Heiser, 2010; Gomez *et al*., 2012) [35, 48], in which system-level power models of Bluetooth and Wi-Fi coexistence on dual-mode devices show aggregate radio current driven by duty cycle, packet size, and coexistence mode (Quainoo & Ogundapo, 2026a) [102], and in which lightweight predictive control of duty cycling under uncertain energy availability has been shown to be feasible on-device (Asiedu, Quainoo, & Asiedu, 2026) [29]. And privacy by architecture: raw signals stay as local as function permits, transported representations are minimized, and every remote consumer is an authorized, logged relationship (Kotz *et al*., 2016; Avancha *et al*., 2012) [60, 30], following privacy-centric security engineering practice (Okoruwa *et al*., 2020) [81], identity-centric zero trust authorization (Ogbole *et al*., 2021) [78], federated identity and access management across heterogeneous environments (Mbonu, Aliliele, Iwuanyanwu, & Uzoka, 2020) [70], and explicit legal and ethical risk modeling of the data protection obligations involved (Mbonu, Aliliele, Iwuanyanwu, & Oluoha, 2018) [69].

4. Architecture Overview

The layer is realized as four cooperating services centered on the phone as reference and gateway. The time alignment service owns per-device clock models: for each connected sensor it runs periodic timestamp exchanges over the device link, estimates offset and drift with uncertainty, and publishes a monotone mapping used to stamp every incoming sample with reference-time bounds. The stream alignment service consumes stamped samples into per-signal buffers ordered on the reference timeline, serves windowed views with resampling where consumers require uniform grids, and enforces fusion gating: multi-signal requests declare tolerance, and the service answers only over intervals whose joint alignment uncertainty satisfies it, otherwise returning explicit not-alignable status. The delivery service exposes the aligned world to consumers, on-phone applications through local interfaces, and remote dashboards, services, and household companions through persistent full-duplex sessions with the semantics of Section 6, in the tradition of scalable and secure architectures for enterprise messaging (Ahmed & Odejobi, 2018a) [7] and of constraint-satisfaction approaches to allocating the resources such sessions consume (Ahmed, Odejobi, & Oshoba, 2019) [8]. The reconciliation service maintains the durable record as a replicated dataset with the merge semantics of Section 7, absorbing buffered histories from devices and reconciling with the remote replica whenever connectivity permits. The services share one design grammar: contracts carry uncertainty and sequence identity, every boundary is measurable in the way that key-indicator frameworks for service delivery require of any component that can be held to an objective (Edivri & Oteri, 2024) [40], and degradation is explicit rather than silent.

5. Time and Stream Alignment Services

The time service adapts sensor network synchronization to the consumer link. Exchange rounds piggyback on existing connection events where the radio protocol allows and run as lightweight request-response probes otherwise, collecting paired timestamps whose asymmetry the estimator treats as noise with link-specific priors (Ganeriwal *et al*., 2003; Gomez *et al*., 2012; Quainoo, Ogundapo, & Asiedu, 2024) [46, 48, 104]. Per device, offset and drift are estimated by robust regression over a sliding exchange history, in the drift-compensating tradition of network-wide protocols (Maróti *et al*., 2004; Mills, 1991) [68, 71], with uncertainty propagated from exchange variance and inter-probe interval; sleep and reconnection reset variance rather than the model, so bounds widen honestly across gaps and tighten as evidence returns, an approach whose closest analogue is epoch-aligned coordination in networks where nodes routinely lose power between exchanges (Asiedu & Quainoo, 2025) [27]. Probe cadence is adaptive: it rises when drift estimates are unstable or an application declares tight tolerance, and falls to near zero when bounds comfortably exceed requirements, spending energy only for accuracy someone needs (Carroll & Heiser, 2010; Sundararaman *et al*., 2005) [35, 113], and the cadence controller itself is a lightweight predictive policy of the kind demonstrated for intermittent devices under uncertain energy availability (Asiedu, Quainoo, & Asiedu, 2026) [29], sensitive to the coexistence and channel conditions that determine what a probe actually costs (Quainoo & Ogundapo, 2026a; Quainoo, Ogundapo, & Asiedu, 2025a) [102, 105].

The stream service builds fusion-ready structure on the stamped streams. Buffers admit out-of-order arrival by design, with completeness managed by watermarks in the event-time manner, a view at reference time t is served when all contributing streams have advanced past t or their absence is declared (Akidau *et al*., 2015) [11]. Resampling to uniform grids uses interpolation appropriate to signal class, with event-type signals, detected beats foremost, never resampled but carried as timestamped events whose analytics require the tightest bounds (Task Force, 1996; Pan & Tompkins, 1985) [114, 97]. Curation policy is explicit at this boundary rather than implicit downstream, following the case for context-aware data curation in any pipeline whose outputs feed learned models (Oyesiji, Nwakamma, & Ojukwu, 2024) [96]. The gating contract is the service's point: fusion consumers, pulse-arrival computations joining electrocardiographic and optical channels (Allen, 2007) [18], respiration estimators fusing modulations (Charlton *et al*., 2018) [36], artifact gates joining optical and inertial streams (Zhang *et al*., 2015) [117], state their tolerance and receive either data within it or a refusal that names the binding constraint, converting alignment quality from an invisible assumption into an observable, loggable property of every derived value (Gravina *et al*., 2017; King *et al*., 2017) [49, 58]. Where inference runs on the handset rather than in the service, the same gated views feed compressed on-device models, keeping raw physiology local by construction (Nwakamma *et al*., 2025) [73].

6. Delivery Service

Delivery follows the persistent-channel discipline with health-specific typing. Sessions are full-duplex over the standard protocol (Fette & Melnikov, 2011) [44], carrying four message types: sample batches, aligned, stamped, and sequence-numbered per stream; derived events, threshold crossings, detections, and quality transitions, individually sequence-numbered; alignment-state notices, publishing per-device uncertainty so remote consumers can gate exactly as local ones do; and control messages for subscription and acknowledgment. Resumption is snapshot-plus-delta: a reconnecting consumer receives current state, latest samples per subscribed stream, active alignment bounds, then ordered deltas from its acknowledged sequence, with replay bounded and gaps surfaced as explicit discontinuity events. Backpressure is type-differentiated: sample streams conflate to freshest-within-window for consumers that fall behind, since superseded physiology serves no live consumer, while derived events queue reliably, since each is individually meaningful, the same asymmetry that governs the reconciliation service's guarantees. Consumer-side rendering of these two classes is the well-understood pattern behind live dashboards and monitoring surfaces in operational and public health settings (Basnet, Oghenemaiga, & Anene, 2023; Orise & Niniola, 2022; Oparah, Ezeh, *et al*., 2023) [31, 89, 86], and concurrency behavior under many simultaneous subscribers is a measurable property of the hosting platform rather than an assumption (Odejobi & Ahmed, 2018b; Ahmed & Odejobi, 2018a) [77, 7]. Transport evolution is tracked at this boundary alone: migration-capable multiplexed transports slot beneath the session semantics without changing them (Iyengar & Thomson, 2021; Langley *et al*., 2017) [55, 64], path diversity and failover at the network edge are the operator's concern rather than the layer's (Ogunwola, 2026) [79], portable execution formats allow the same processing to run either side of the boundary (Ojukwu, Oyesiji, & Nwakamma, 2025) [80], deployments with many concurrent consumers interpose a durable log behind the service without changing device-side behavior (Kreps *et al*., 2011) [61], and availability commitments to consumers are stated as service assurance objectives rather than left implicit (Oteri & Edivri, 2026) [95]. Where the delivery path terminates in an alert to a person rather than to a program, the alerting literature's requirements on trust, comprehension, and accessibility govern the final hop (Odejide, 2024, 2025) [75, 76].

7. Reconciliation Service

The record is specified as a replicated dataset with convergent merge semantics. Observations, samples, events, annotations, are immutable, uniquely identified by source, stream, and reference-time bounds, and merged by set union, making observation history a conflict-free replicated grow-set whose convergence is guaranteed by construction (Shapiro *et al*., 2011) [108]. Mutable state, device registrations, consumer subscriptions, user annotations subject to edit, uses register semantics with deterministic resolution declared per field, and every resolution retains the losing value in provenance, following the reconciliation lineage in which conflicts are detected and resolved by policy rather than by accident of timing (Terry *et al*., 1995; DeCandia *et al*., 2007; Kleppmann, 2017) [115, 38, 59]. Anti-entropy runs opportunistically: device buffers flush into the phone replica on connection, phone and service replicas exchange digests and deltas on any network availability, and convergence is verified by digest comparison, with partitions bounded in effect by the availability-consistency constraints the design accepts explicitly, availability and partition tolerance for observations, with consistency restored by merge (Gilbert & Lynch, 2002; Brewer, 2012) [47, 34]. Provenance is durable and independently checkable, which is the property immutable audit-trail and configuration-attestation designs are built to supply (Oshoba, Hammed, & Odejobi, 2020) [94], and the governed storage layer beneath it follows lakehouse governance and loss-prevention practice (Aliliele *et al*., 2025b) [17] with sensitivity classification determining retention and export eligibility per field (Aliliele, Mbonu, & Iwuanyanwu, 2024a) [15]. Access to replicas is mediated by federated identity and attribute-based authorization rather than by network position (Oshoba, Hammed, & Odejobi, 2019; Shittu & Nabil, 2023; Ogbole *et al*., 2021) [93, 110, 78]. The record's exit interface maps the converged dataset onto standard health resources for authorized export, placing the layer inside the interoperability ecosystem rather than beside it (Bender & Sartipi, 2013; Mandel *et al*., 2016; Ilodigwe & Adesemoye, 2021) [32, 67, 52], and every export, like every remote subscription, is an authorized, minimized, logged flow under the privacy requirements (Kotz *et al*., 2016; Avancha *et al*., 2012; Afrihyia, Ojukwu, & Akinse, 2024; Aliliele, Mbonu, & Iwuanyanwu, 2024b) [60, 30, 6, 16] and the cross-jurisdictional obligations that attach to health data in particular (Ominyi & Anichukwueze, 2022a; Annan, 2022) [83, 22].

8. Evaluation Plan

Evaluation is phased along the stack. Phase one measures alignment. Across a device matrix spanning link types and device classes, achieved clock-model accuracy is evaluated against ground truth from a shared physical stimulus observable by all devices under test, with error and bound-honesty, the fraction of truth within published bounds, reported per device class, probe cadence, and gap length, situating the consumer topology against the accuracy regimes the sensor network literature achieved in its own (Elson *et al*., 2002; Maróti *et al*., 2004; Ganeriwal *et al*., 2003) [42, 68, 46]. The measurement apparatus itself follows wireless hardware engineering practice, in which scripted instrument control and automated test frameworks are what make timing claims reproducible across a device matrix at all (Quainoo, Ogundapo, & Asiedu, 2025b) [106], and in which transceiver-level test methodology is the accepted basis for comparing devices whose radio subsystems differ (Quainoo & Ogundapo, 2026b) [103]. Phase two measures the composed data path: end-to-end latency from sample acquisition to local consumer and to remote consumer, decomposed per service; delivery semantics under scripted disconnection, verifying gapless persisted records, correct snapshot-plus-delta behavior, and the conflate-versus-queue contract per type (Fette & Melnikov, 2011; Pimentel & Nickerson, 2012) [44, 100]; reconciliation convergence time and correctness under partition schedules, including multi-day device buffering, evaluated in the way simulation studies of large-scale intermittently powered networks evaluate reliability under power gaps (Asiedu & Quainoo, 2023b) [25]; load and capacity behavior as consumer counts scale, using the forecasting and capacity-planning methods established for multi-stakeholder platforms (Edivri & Oteri, 2022; Ahmed, Odejobi, & Oshoba, 2020) [39, 9]; and energy cost on representative hardware across probe and streaming policies (Carroll & Heiser, 2010; Quainoo & Ogundapo, 2026a) [35, 102].

Phase three measures what synchronization buys. Representative multi-sensor computations, beat-interval analytics, pulse-arrival timing, fusion-gated artifact rejection, are evaluated with the layer's alignment versus naive arrival-time alignment, quantifying downstream error as a function of alignment error and validating the gating tolerances against the signal literatures' requirements (Task Force, 1996; Allen, 2007; Charlton *et al*., 2018; Zhang *et al*., 2015; Bent *et al*., 2020) [114, 18, 36, 117, 33]. Because the derived values in question are the inputs to risk models and decision support, the phase reports their sensitivity to alignment error in the terms those downstream systems use (Okwah, 2022; Amadi *et al*., 2025; Adelanwa, Basnet, & Anene, 2024a) [82, 19, 2], and lifecycle performance measurement supplies the framing for reporting improvement attributable to an infrastructure change rather than to the applications above it (Adelanwa, Basnet, & Anene, 2023a; Ilodigwe & Adesemoye, 2024a) [1, 53]. The phase's endpoint is the concept's justifying claim rendered measurable: that alignment uncertainty, made explicit and enforced, changes the validity of derived health measures by margins that matter to their consumers (Gravina *et al*., 2017; Coravos *et al*., 2019) [49, 37].

9. Anticipated Applications

The layer is infrastructure, and its applications are the application classes above it. Real-time feedback and just-in-time intervention consume the delivery service's bounded-latency events with alignment-gated validity (Nahum-Shani *et al*., 2018) [72], and where those events escalate to human-facing alerts, accessibility and trust requirements govern the last hop (Odejide, 2023, 2024) [74, 75]. Multi-sensor measurement applications, cardiovascular timing analytics, respiration estimation, activity-contextualized physiology, consume the stream service's gated fusion views, gaining the validity qualification they currently lack (Allen, 2007; Charlton *et al*., 2018; King *et al*., 2017) [18, 36, 58], which matters most where the derived indices carry clinical weight (Okwah, 2022; Amadi *et al*., 2025) [82, 19]. Care delivery applications consume the reconciled record: structured monitoring protocols whose value depends on complete and correctly ordered observations (Akinlolu, Omaghomi, & Fapohunda, 2025) [13], care coordination programs aimed at reducing avoidable readmission (Akinlolu *et al*., 2023) [12], and cross-unit response coordination where timing is the coordinating variable (Fapohunda *et al*., 2025a) [43]. Longitudinal and clinical-adjacent applications consume the reconciled record and its standards-based export, from self-tracking through remote monitoring programs to research data collection with ecological instruments (Steinhubl *et al*., 2015; Mandel *et al*., 2016; Shiffman *et al*., 2008; Oparah, Gado, *et al*., 2021; Oparah, Gado, *et al*., 2024b) [112, 67, 109, 87, 88], and population-level surfaces aggregate from the same converged records (Anioke & Atima, 2023b; Ilodigwe & Adesemoye, 2024a) [20, 53]. And device ecosystems benefit structurally: because contracts are per-service, vendors can integrate at the boundary their devices support, contributing stamped streams without adopting the whole stack, which is how infrastructure layers spread (Kleppmann, 2017) [59]; the same argument holds in adjacent multi-agent settings where fleets of independently clocked units must act on a shared timeline (Akanbi, Ganiu, & Sunday, 2025) [10].

10. Limitations

The concept's bounds are concrete. Alignment accuracy is floored by link access: without media-layer timestamping, consumer radio stacks impose exchange asymmetries that no estimator removes, so achievable bounds are device-class facts to be measured, not targets to be assumed, and some tight-tolerance computations will remain out of reach on some hardware (Gomez *et al*., 2012; Sundararaman *et al*., 2005; Quainoo, Ogundapo, & Asiedu, 2024; Quainoo, Ogundapo, & Asiedu, 2025a) [48, 113, 104, 105]. Ground-truth evaluation itself is nontrivial at millisecond scales and shapes phase one's stimulus design, and is only as reproducible as the instrument-control tooling behind it (Quainoo, Ogundapo, & Asiedu, 2025b) [106]. The reconciliation guarantees cover the record's convergence, not its truth: duplicated devices, corrupted buffers, and clock model failures produce well-merged wrong data, which the provenance and bound-honesty machinery makes detectable but not impossible (Aliliele, Mbonu, & Iwuanyanwu, 2024a; Oshoba, Hammed, & Odejobi, 2020) [15, 94]. Energy adaptivity trades accuracy for battery by design, and the policy surface it exposes can be mis-set by integrators; defaults and guardrails are part of the deliverable but not a proof against misuse (Asiedu, Quainoo, & Asiedu, 2025; Asiedu & Quainoo, 2024) [28, 26]. Where derived values feed automated decisions, accountability for those decisions sits above this layer and is governed by regimes the layer can support but not satisfy (Annan, 2024; Ominyi & Anichukwueze, 2024; Ominyi, Anichukwueze, & Uzougbo, 2024b; Afrihyia, Akinse, & Ojukwu, 2024) [23, 84, 85, 5]. Equity of access is likewise out of scope and not out of consequence, since a layer that assumes a capable handset and a modern radio inherits whatever exclusion those assumptions carry (Orise & Niniola, 2024; Odejide, 2025) [91, 76]. Finally, the layer's privacy posture governs flows it mediates and cannot govern applications above it; minimization and authorization at the boundary are necessary, not sufficient, for the health-data stewardship the setting demands (Kotz *et al*., 2016; Avancha *et al*., 2012; Orise & Niniola, 2023, 2025; Mbonu *et al*., 2018) [60, 30, 90, 92, 69].

11. Conclusion

This paper has developed a research concept for low-latency biometric synchronization as a specified layer for digital health applications: clock alignment with honest uncertainty, stream alignment with tolerance-gated fusion, delivery with typed, resumable, backpressure-aware sessions, and record reconciliation with convergence guaranteed by construction. The design transfers mature instruments, sensor network time synchronization, event-time stream semantics, persistent full-duplex channels, and convergent replicated data types, into the phone-centered, intermittently connected, privacy-constrained topology that digital health actually inhabits, and binds them with one discipline: uncertainty and sequence identity travel with the data, and every boundary either meets its contract or says so.

The evaluation plan makes the layer's value empirical, measuring achievable alignment per device class, latency and convergence under realistic disruption, and the downstream validity gains for multi-sensor computation that justify the machinery. If borne out, the concept gives digital health engineering what it currently improvises per application: a synchronization substrate on which timing-sensitive measurement is valid by contract, timely by budget, and convergent by design, the quiet infrastructure that the field's clinical ambitions presuppose.

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