Review

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Review

From Integrated Care to Learning Systems

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Abstract

Integrated care is increasingly shaped by digital infrastructures, data governance, and AI-enabled analytics, yet the relevant literature remains fragmented across health-services research, digital health, and machine learning. This article presents a conceptual review informed by structured scoping searches across PubMed, Scopus, Semantic Scholar, Crossref, and selected policy sources covering January 2001–March 2026. The search component was used to map the field and identify representative frameworks, implementations, and technical advances rather than to estimate pooled effects. We synthesise the literature across four domains: conceptual foundations of integrated care, AI and multimodal analytics, implementation barriers, and digital-governance requirements. On that basis, we propose a five-level taxonomy ranging from disease-specific programmes to learning integrated care models and argue that most current deployments remain concentrated at digitally integrated but only weakly adaptive Type IV configurations. Across the literature, three recurrent constraints limit progression towards Type V learning systems: temporal blind spots, maintenance debt, and governance misalignment. Overall, the review positions AI-enabled integrated care less as a finished model than as an emerging design space requiring longitudinal data assets, stewarded model lifecycles, and accountable governance to support clinically useful, equitable, and trustworthy learning systems.

Keywords: integrated care; artificial intelligence; multimodal learning; learning health systems; data governance; conceptual review

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1. Introduction

Health systems worldwide are facing a demographic and epidemiological inflection point. By 2050, one in six people globally will be aged 65 or older [1], and in the European Union, this proportion will approach one-third of the population [2]. Life expectancy continues to increase, yet so too does the prevalence of multimorbidity, frailty, and cognitive decline [3]. These shifts are straining systems historically optimised for acute, episodic interventions. Traditional disease-centred models, organised around specialities and institutions rather than individuals, are proving inadequate for the long-term coordination and prevention required by ageing societies [4,5]. Recent 2026 demographic work reinforces this conclusion: population ageing is no longer a siloed policy issue, because care demand, workforce pressure, and social dependency now interact across the sectoral boundaries that integrated care is meant to bridge [6].

Parallel to population ageing, non-communicable diseases (NCDs) now account for nearly three-quarters of global mortality, with cardiovascular, oncological, metabolic, and respiratory disorders constituting the largest share [7]. People increasingly live longer with several chronic conditions that demand continuity of care across multiple domains. Disconnected data systems, episodic financing, and institutional silos continue to limit both efficiency and equity in care delivery [8]. The resulting mismatch between complex patient needs and the structural logic of healthcare organisations produces duplication, waste, and inequitable outcomes.

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Empirically, care fragmentation is associated with higher utilisation, more avoidable hospitalisations, and medication safety risks, especially for older adults with multimorbidity [5,9–11]. Cross-regional analyses suggest a sizeable share of variation in fragmentation is unrelated to clinical need, implying remediable system design factors [12]. Recent national studies from Denmark confirm that greater fragmentation correlates with potentially inappropriate medication and increased mortality risk [13]. It is therefore useful to distinguish between continuity (seeing the right people at the right time) and coordination (those people working from the same plan and data). Both are necessary, and both suffer when digital and organisational seams are misaligned [14].

A parallel crisis is unfolding in the health-care workforce. The supply of professional and informal caregivers is insufficient to meet rising demand, particularly in high-income regions. The OECD projects a shortfall exceeding ten million long-term-care workers by 2040 [15]. Informal caregivers, family members and friends, increasingly absorb responsibilities without training or compensation [16]. These pressures highlight systemic inequities in how societies value care and show that expansion of existing services is no longer sustainable. Addressing them requires changes in service organisation, workforce support, and care coordination.

In response, major jurisdictions have formalised integration as both moral and economic necessity. We emphasise three anchor frameworks that directly shape learning ecosystems: WHO's Integrated, People-Centred Health Services (IPCHS), the UN Decade of Healthy Ageing, and the European Health Data Space (EHDS) [17–19]. Additional policy instruments (for example, the EU Green Paper on Ageing, the European Care Strategy, national legislation, and regional standards) are summarised in Supplementary Material. Together, these frameworks support more coordinated and data-enabled care across sectors. Yet, despite two decades of policy, most integration remains brittle, too dependent on projects, personalities, and pilots to sustain continuity as needs evolve.

Despite reform efforts, however, care delivery remains largely disjointed [9]. Patients, particularly those with multimorbidity, navigate multiple specialists, each operating within separate organisations, budgets, and information systems [4]. This fragmentation generates three recurrent failures: duplication and inefficiency, gaps in continuity, and inequitable access [8,10]. Redundant diagnostics, conflicting prescriptions, and misaligned care plans inflate costs and risk, while poor information transfer between providers undermines safety. Vulnerable groups, older adults, migrants, rural residents, bear disproportionate consequences.

Consequently, policymakers increasingly view integration not as managerial reform but as a clinical and digital imperative. Integrated Care Models (ICMs) replace fragmentation with connectivity, aligning incentives, information, and accountability around the individual [20,21]. Shared information flows and coordinated decision-making across prevention, treatment, rehabilitation, and community support can reduce fragmentation and improve continuity, quality, and equity [22,23]. Still, most deployed models plateau at digital integration, dashboards, data-sharing, and one-off analytics (Type IV), rather than embedding adaptive learning into the governance layer itself (Type V). In practice, integration requires moving from institution-centred treatment episodes towards networked, data-informed, and longitudinal care. However, that transition remains incomplete.

The present review consolidates current evidence and emerging directions at the intersection of health-system design, data governance, and digital innovation. It addresses four guiding questions: (1) How have ICMs evolved conceptually, and what frameworks underpin them? (2) What digital infrastructures and analytical tools enable integration across domains? (3) Which evaluation methods best capture clinical, economic, and equity impacts? and (4) How can lessons from global implementations inform sustainable scaling?

Through this synthesis, the review examines how ICMs are being shaped by data governance, digital infrastructure, and AI, with particular attention to clinical outcomes, equity, and implementation constraints. This tension—Type IV systems that integrate but do not learn—sets up the central question addressed in Sections 4–6: how to move from static integration to adaptive intelligence. To anchor the discussion, we draw on comparative evidence across jurisdictions. Reviews of integrated care for older

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adults emphasise core design features, multidisciplinary teams, shared care plans, and community linkages, while warning that benefits erode without stable governance and data foundations [24,25]. Long-run country experiences (for example, the Netherlands) show that meaningful integration is the product of sustained, multi-instrument policy over a decade, not a single reform [26]. Conceptual syntheses likewise caution that "integrated care" is plural, an umbrella spanning disease programmes, population segments, whole systems, digital platforms, and learning ecosystems [27,28]. Recent empirical studies further show how heterogeneous current implementations remain: digitally supported primary-care models in Europe, integrated home-care services in Italy, patient-centred medical homes in Singapore, community palliative pathways in the UK, rural atrial-fibrillation programmes in China, and intelligent older-adult care models all report some combination of continuity, quality-of-life, or utilisation gains, but with markedly different digital depth and governance maturity [21,29–33]. We use this pluralism to motivate the Type I–V taxonomy and the case for elevating learning onto the governance layer.

2. Review Approach and Search Strategy

2.1. Scoping Search Design

We undertook a conceptual review informed by structured scoping searches. The objective was not to produce a formal systematic review or pooled-effect meta-analysis, but to map the literature sufficiently to identify anchor frameworks, representative implementations, and emerging technical directions at the intersection of integrated care, digital health, and AI. For transparency, we report the search architecture, screening logic, and corpus sizes used to inform the final narrative synthesis. Full operational search blocks, screening workflow, extraction fields, and taxonomy-coding rules are reported in the Supplementary Material (Section S1). To capture the evolution of ICMs from policy frameworks to AI-enabled systems, we structured the search strategy across three conceptual tiers:

- **Tier 1, AI-intensive corpus:** focused on machine learning, deep learning, predictive analytics, and multimodal decision support applied to healthcare and chronic-care delivery.
- **Tier 2, ICM-core corpus:** targeted classical and digital ICMs, continuity of care, people-centred and value-based frameworks, including policy and governance perspectives.
- **Tier 3, Transitional corpus:** bridged the two domains, capturing digital integrated care, learning healthcare systems, and data-driven or AI-enabled organisational models.

Literature included in the review spanned January 2001–March 2026. Core literature searches were performed in PubMed, Scopus, Semantic Scholar and Crossref, with targeted forward screening used to capture newly emerging studies from the most recent period. Across the core sources, 5 930 records were identified. After DOI-first and title-similarity deduplication, 1 427 duplicates were removed, leaving 4 503 unique records for initial screening. The screened pool was organised as Tier 1 = 1 675 records, Tier 2 = 2 023 records, and Tier 3 = 805 records. These buckets reflect the review's search architecture rather than mutually exclusive substantive literatures. Grey literature, including policy frameworks from the WHO, OECD, and European Commission, was included where provenance and policy relevance were explicit. Existing citations from the project's reference library (n = 150) were cross-checked, and 27 exact DOI matches plus 18 high-similarity entries were retained where they added foundational or policy context.

2.2. Screening, Synthesis, and Supplementary Policy Frameworks

Title and abstract screening was used to prioritise conceptually rich and methodologically transparent sources for full-text reading. In total, 620 full texts were examined to inform the synthesis. The final manuscript cites 192 sources judged most relevant to the review's conceptual aims; within this set, 84 empirical implementation or evaluation studies were foregrounded when grounding claims about deployment and outcomes. We do not present these studies as a standalone quantitative synthesis, and numerical findings are discussed selectively rather than pooled. A PRISMA-style audit trail of identification, screening, and inclusion is provided in Supplementary Figure S1.

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Beyond the three anchor frameworks referenced in the Introduction, additional policy instruments cited in the literature include the EU Green Paper on Ageing and the European Care Strategy, the U.S. 21st Century Cures Act, WHO's ICOPE guidance and regional integrated-care standards, and national or provincial tools such as Canada's people-centred standards and Asia–Pacific digital-health strategies [34–39]. A consolidated summary is reported in Supplementary Section S3.

3. Conceptual Foundations of Integrated Care

Integrated care evolved to address a structural mismatch: twentieth-century systems optimised for acute episodes now face ageing, multimorbid populations requiring continuity across health and social domains. The Chronic Care Model (CCM) [4,5] introduced six levers—self-management support, delivery-system design, decision support, information systems, community resources, and organisational leadership—that shifted care from reactive silos to productive patient–clinician partnerships. WHO's Integrated, People-Centred Health Services (IPCHS) framework [17] expanded this logic to entire systems, foregrounding equity, governance, and community voice. Digital transformation recast integration as an information and learning problem, with multilayer interoperability [8], federated data spaces [19], and predictive models converging under General Data Protection Regulation (GDPR)-aligned governance [10,40].

From a programme perspective, most implementations can be mapped to one of five archetype levels. **Type I** initiatives focus on single-disease management (diabetes, heart failure) with siloed data. **Type II** extends coordination to cohort-based segments (frail elderly, complex multimorbidity) yet remain clinically centred. **Type III** models achieve whole-system alignment, shared budgets, joint governance, cross-sector partnerships, but often lack adaptive digital infrastructure. **Type IV** wires electronic health records (EHRs), registries, and dashboards for real-time visibility. Analytics support risk stratification and care-pathway optimisation. Useful progress, yet these tiers remain essentially static. **Type V** introduces a learning loop: continuous multimodal monitoring (trajectories across years, not snapshots), federated AI that adapts as populations and practices shift, transparent data-trusts under outcome-based contracts, and explicit human–AI symbiosis where models reshape with clinician feedback. *In this review, we use "learning loop" to mean continuous model updating based on multimodal longitudinal feedback under governed deployment.* In real-world deployments, Type V remains rare because incentives reward volume over longitudinal outcomes, model stewardship is under-resourced, and trajectory-level data (frailty progression, care-dependency transitions, cognitive decline) are under-measured. It is this gap—between digital wiring (Type IV) and feedback-driven learning (Type V)—that the COMFORTage approach directly targets [41] (see Supplementary Material for the full taxonomy). The Type I–V scheme is used here as an analytical framework developed through iterative comparison of the scoping corpus, foundational integrated-care models, and recent digital/AI deployments; it is intended to clarify variation in maturity rather than serve as a formally validated classification instrument.

4. AI and Machine Learning in Integrated Care Models

If the conceptual gap is the leap from static to learning systems, then artificial intelligence provides the engine. AI now sits inside the plumbing of integration, not as a novelty, but as a way to sense, forecast, and coordinate across boundaries that clinicians on the ground know all too well. Modern ICMs rely on machine-learning and deep-learning (DL) systems that transform heterogeneous health data into timely signals. When these signals are wired into workflows, teams can intervene earlier, care plans converge, and avoidable deterioration is reduced [4,5,8]. AI extends the chronic-care logic by embedding adaptive intelligence within the digital layer that connects prevention, diagnosis, and treatment.

AI's contributions typically fall into four functional domains: (i) **population-level analytics** for risk stratification and resource allocation [11,42]; (ii) **clinical decision support (CDS)**, which translates multimodal inputs into diagnostic or prognostic recommendations [43,44]; (iii) **operational optimisa-**

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tion for patient flow and scheduling [45,46]; and (iv) **patient-facing intelligence** via conversational agents and self-management apps [47,48]. These functions map to the layered structure of integration: macro (population health), meso (organisational coordination), and micro (patient interaction). The goal is not to replace judgement but to reduce blind spots and latency, especially at care transitions. The proliferation of multimodal data—from imaging and genomics to wearables and social signals—has pushed architectures towards learning unified, cross-modal representations [43,49,50]. More recently, federated, privacy-preserving training has allowed institutions to collaborate on model development without centralising sensitive raw data, an approach that aligns with EHDS principles [19,51]. This approach reduces site-specific bias and lets models refresh quickly as real-world clinical and behavioural patterns shift. Early 2026 perspectives on digital-intelligent precision health management and integrated cardiorenal transitional care reinforce the same design lesson: multimodal sensing, remote monitoring, and adaptive decision support create most value when they are embedded across prevention, acute care, and follow-up, rather than deployed as isolated digital layers [52,53].

Under the hood, several technical currents have matured to make these functions practical in ICMs. For longitudinal prediction, dynamic and high-frequency EHR models outperform static baselines and can surface early decompensation signals in intensive care and ward settings [54–56]. Representation learning over routine EHRs, combining codes, labs, notes, and physiology, improves sample efficiency and portability across sites [57,58]. At the system level, "big-data" population analytics have long identified high-risk, high-cost cohorts; recent work extends this to proactive pathway optimisation and resource targeting [59]. In parallel, unified multimodal frameworks and surveys show consistent incremental gains when fusing text, time-series, imaging, and structured data, an increasingly common scenario in integrated care [50,60,61]. For neurocognitive trajectories, graph and imaging models personalise risk and explanation [44,62,63].

Two additional threads matter for real-world deployment. First, automation of model development and adaptation: AutoML can compress development cycles, while meta-learning and reinforcement learning help models adapt to new tasks, domains, and feedback constraints that are endemic in multi-site ICMs [45,46,64]. Second, transparency and safety: explainability toolkits and multimodal, multi-centre fusion studies clarify what different methods can and cannot claim, especially under feature collinearity and model updates [65–69]. The practical lesson is to design for stewardship from the start: treat model monitoring, drift detection, and explainability checks as part of routine operations, not afterthoughts.

Beyond these functional categories, however, learning systems must track trajectories over time. For ageing populations, this includes frailty progression, care-dependency transitions, and cognitive decline. Behavioural analytics from wearables and home sensors add context to clinical measures, often explaining why individuals with similar biomedical profiles diverge in function. In practice, clinicians need earlier, more actionable signals—weeks before deterioration, not hours. Type V designs treat these trajectories as first-class objects, linking multimodal features to life-course patterns rather than isolated episodes.

AI adoption also depends on trust. Techniques such as SHAP and LIME can make model behaviour more legible to clinicians [65,69], but transparency without bias control is insufficient because demographic skews in training data can harden inequities [10,40]. Accountability and stewardship are therefore central as ICMs with embedded AI blur institutional boundaries. Co-creation with patients, transparent data flows, and shared value are increasingly expected. Thousands of algorithms show promise, but few reach routine use because they are not designed for the operational realities of clinical work [47,70]. Operational experience shows that dashboards age poorly, models drift, data definitions change, and workflows evolve. Type V systems therefore need explicit drift monitoring, retraining routines, and documented model change. This maintenance burden leads directly to the learning ecosystems discussed next.

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5. Implementation Barriers and Learning Gaps

Stepping from methods and models to practice, the evidence shows a stubborn pattern: many initiatives integrate digitally (Type IV) but fail to create systems that learn (Type V). The gap is not in digital ambition but in operational reality. Implementations stall at handoffs, semantics, and maintenance, while evaluation often misses the dynamics of a working learning loop. This section synthesises operational evidence to frame the gap that learning ecosystems must close. Extended examples are in Supplementary Material. Recent 2026 commentary on clinical AI deployment underscores the organisational challenge: redesigning leadership, incentives, and learning culture may determine whether technically capable systems remain pilots or move into routine care [71].

A growing implementation literature helps to explain this plateau. Across 34 empirical deployments, common determinants of success include basic IT readiness, stakeholder engagement, fit with workflow, and visible leadership, while barriers cluster around perceived complexity and lack of evaluation routines [72]. Bibliometric scans and management-oriented reviews confirm the enthusiasm–realisation gap: activity is rising, but most AI initiatives remain early-stage pilots with limited longitudinal outcomes and modest operational integration [47,73,74]. Meanwhile, technical progress can outrun social systems: transformer-based natural language processing (NLP) and foundation-model pipelines raise auditability, privacy, and workforce concerns that must be addressed explicitly in ICM governance [75]. Longitudinal EHR studies demonstrate clinical potential for earlier detection and prevention, but translation requires resourcing the maintenance loop and aligning incentives towards long-term outcomes [76].

In real settings, coordination, evaluation, and engagement each introduce their own failure points. Integrated care hinges on multidisciplinary teams (MDTs) with shared information and goals. Recent studies of integrated home care, patient-centred medical homes, community palliative care, rural cardiovascular pathways, and intelligent older-adult support programmes reinforce the same point: digital tools matter only when they are woven into local coordination routines, continuity arrangements, and workforce practice [29–33]. While shared care plans and interoperable records demonstrably reduce avoidable hospitalisations, clinicians report recurring pain points: handoffs fail when semantics diverge and shared plans drift from reality. AI-assisted triage and scheduling can help, but only when they reflect local constraints and are auditable [45,46,75]. Human-in-the-loop safeguards and targeted explanations are essential to preserve clinical autonomy and trust. The friction is not a sign of failure but a design requirement for Type V systems, which must anticipate and adapt to these real-world dynamics. The same pattern appears in frailty assessment: a 2026 hospital-based analysis from Japan found uneven uptake across departments and care processes despite broad recognition of frailty as a core ageing construct [77].

Meanwhile, evaluation needs to move beyond static accuracy to capture system change. Core outcomes remain vital (avoidable admissions, emergency department (ED) visits, readmissions, cost per capita, patient-reported outcome measures (PROMs) and patient-reported experience measures (PREMs)). However, to measure a learning system, we need learning-cycle Key Performance Indicators (KPIs): (i) *learning-cycle latency* (time from drift detection to validated redeployment); (ii) *explainability compliance* (share of decisions with fit-for-purpose rationale); (iii) *fairness gap* (residual disparity after mitigation); and (iv) *model provenance* (traceable lineage across versions). Health Technology Assessment (HTA) for such systems must likewise evolve to assess interoperability, lifecycle maintenance, and equity impacts [8,65,69]. Mature ICMs tend to generate savings by preventing deterioration and duplication; caregiver relief adds significant social value that traditional models often miss.

Equally important, person-centredness requires genuine agency: shared decisions, accessible tools, and participation that counts. While digital platforms can widen access, they can also exclude. Targeted literacy support and assisted navigation are critical. Governance must institutionalise co-production (patient councils, advisory boards) and routinely monitor equity (stratified outcomes, bias audits) so that digital integration narrows rather than widens health gaps [8,10].

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Many programmes stall at the Type IV plateau, and several issues recur in the evidence. As summarised in Table 1, three recurrent failure modes drive this plateau: (i) **temporal blind spots**—systems are built to see clinical snapshots, not life-course trajectories; (ii) **maintenance debt**—models, data mappings, and workflows are not resourced to evolve; and (iii) **misaligned incentives**—contracts reward activity and volume, not longitudinal outcomes or preventative care. The table pairs each symptom with its underlying cause and the corresponding Type V response: trajectory-aware monitoring and early-warning signals; a stewarded ML lifecycle with drift monitoring, scheduled retraining, and versioned provenance; and outcome-based contracts embedded in trustworthy data-space governance. Together, these failures point to a Type V learning design that prioritises longitudinal data (frailty trajectories, care-dependency transitions), resourced model stewardship, and outcome-based contracts that make learning a shared goal.

Table 1. Why Type IV fails and how Type V responds in Integrated Care Models.

Failure in Type IV	Typical Symptom	Underlying Cause	Type V Response
Temporal blind spots [8,54,76]	Late detection of decline and reactive escalations	Snapshot metrics and episode-centred data	Model for life-course trajectories and early-warning signals from multimodal streams
Maintenance debt [47,70]	Models drift and dashboards become untrusted	No resourced retraining or revalidation	Stewarded ML lifecycle: drift monitoring, scheduled retraining, versioned provenance
Semantic drift [8,78]	Handoffs fail and shared plans diverge	Inconsistent codes/ontologies across sites	Shared ontologies, semantic mediation, and governance for controlled vocabularies
Governance gaps [19,51]	Privacy/security block reuse and stalled collaborations	Compliance-only mindset, unclear roles	Data-trusts and data-spaces with clear access, audit, and shared benefit rules
Appraisal mismatch [8,47]	High AUC (area under the ROC curve), low impact	Metrics ignore workflow fit and equity	Learning KPIs (latency, explainability compliance, fairness gap) alongside outcomes
Engagement as app [8,10]	Low uptake and inequalities widen	Tools without support for agency	Co-production, assisted navigation, and equity monitoring with mitigations

With these failure modes in view, we next outline the digital foundations and governance arrangements required to sustain learning ecosystems at scale.

6. Digital and Governance Foundations

Against these implementation gaps, two foundations matter: the digital plumbing that moves data, and the governance that makes its use trustworthy. The learning systems described above cannot exist without a robust digital foundation. Interoperability—the seamless, standards-based exchange of data among clinical, administrative, and social-care systems—is essential for transforming fragmented services into coordinated pathways. The adoption of standards such as HL7 Fast Healthcare Interoperability Resources (FHIR), openEHR, and SNOMED CT (Systematized Nomenclature of Medicine Clinical Terms) has created a common language for data exchange, enabling real-time

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visibility of patient trajectories across care levels [78–80]. Yet, as multiple analyses reveal, technical standardisation alone is not enough [8]. Organisational and semantic interoperability remain persistent bottlenecks, particularly where legacy systems encode data idiosyncratically or restrict access through proprietary formats.

Recent progress has been driven by platform-based architectures that integrate EHRs, remote-monitoring feeds, and public-health databases within distributed data-spaces. These allow authorised professionals to access context-specific patient views rather than raw data, maintaining privacy while enabling coordination. In Europe, the EHDS exemplifies this shift by introducing a federated model where Member States retain data custodianship while enabling cross-border interoperability through common technical specifications and trust frameworks [19]. Similar architectures in Japan and Canada link hospital systems with long-term-care registries through secure application programming interfaces (APIs), proving that digital alignment can be achieved without full centralisation. Still, the complexity of cross-sectoral data sharing requires sustained investment in infrastructure, metadata curation, and workforce training. Interoperability, therefore, is as much a social and political achievement as a technical one, depending on shared governance and trust between institutions. Early 2026 architectural work pushes this logic further towards modular federated microservices with blockchain-backed audit trails, reinforcing that interoperability, scalable analytics, and accountable access control need to be designed as one infrastructural problem rather than separate layers [81].

Multiple reviews converge on the same bottlenecks: semantic mediation across idiosyncratic source systems, governance that allows privacy-preserving reuse, and incentives for custodians to contribute high-quality data [70,82]. The COVID-19 period supplied a natural stress test; despite heroic workarounds, data-sharing frictions and inconsistent standards slowed response, underscoring the need for pre-positioned infrastructures and playbooks [83–85]. From an architecture perspective, federated learning and cloud-platform coordination can reconcile local control with system-wide learning, provided that access, logging, and audit are first-class citizens [23,51]. The best-performing ICMs pair technical standards (HL7 FHIR/openEHR/SNOMED) with organisational assets (catalogues, contracts, training) to achieve real-world interoperability.

At the same time, governance determines whether these pipes can be used legitimately and at scale. As integrated-care networks accumulate vast, heterogeneous data, the need for robust governance intensifies. Effective governance balances three sometimes-conflicting principles: patient agency, data utility, and system security. Emerging “data-trust” and “data-space” models seek to mediate this balance. Under these arrangements, trusted intermediaries manage consent and access on behalf of citizens, enabling data reuse without relinquishing individual control. The UK’s National Health Service (NHS) Federated Data Platform and Finland’s Findata exemplify how such entities can authorise secondary data use for analytics or innovation while maintaining legal separation from clinical operators. To safeguard equity, ethical oversight committees increasingly integrate algorithmic-impact assessments that scrutinise for bias prior to deployment [65,69]. A 2026 scoping review of differential privacy in medical deep learning shows that clinically tolerable privacy budgets may be achievable, but strict settings and inconsistent reporting can still degrade subgroup performance unless fairness auditing and deployment standards are built into the lifecycle [86].

Cybersecurity is an equally critical dimension. Attacks on hospital infrastructures during the COVID-19 pandemic revealed the vulnerability of even well-resourced systems. Zero-trust architectures and continuous authentication are becoming baseline requirements for connected-care environments [46]. Interoperable governance arrangements are therefore a prerequisite for learning infrastructures. They allow machine-learning pipelines to process multimodal data and support near-real-time clinical and managerial decisions. Federated learning extends this adaptivity across institutions by allowing decentralised training without exchanging raw data, preserving privacy while enabling collective intelligence [51].

Data governance in integrated care must evolve from compliance to stewardship that enables responsible reuse, innovation, and equity. Emerging European debates on *digital personhood* and

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algorithmic solidarity clarify the same requirement: legitimate data reuse depends on demonstrating collective benefit while preserving individual agency, a process audited routinely by data-trusts and access bodies under frameworks like EHDS. Under these conditions, digital infrastructure can support continuous feedback between clinical operations and model performance. A practical governance checklist for Type V programmes thus includes: (i) clear roles for data controllers/processors and trusted intermediaries; (ii) consent and transparency mechanisms appropriate to longitudinal, multimodal analytics; (iii) model lifecycle obligations (drift monitoring, revalidation, versioned provenance, and explainability audits); (iv) equity safeguards that monitor and mitigate residual gaps across subgroups; and (v) reciprocal value frameworks so contributing sites and citizens see tangible benefit [40,65,69]. Embedding these expectations in contracts and oversight bodies reduces the uncertainty that often stalls cross-sector data collaboration and unlocks the learning benefits of scale. These governance conditions frame the broader synthesis taken up in the Discussion.

7. Discussion

The convergence of ICMs and AI adds a cognitive layer to integration. Predictive models, decision support, and feedback loops can anticipate need and coordinate action across settings. The central question is whether these capabilities are embedded in workflows that can learn over time. Two balances matter. First, human–AI symbiosis: AI should widen clinicians' field of view and compress reaction time, not crowd out judgement. Second, temporal continuity: systems must recognise trajectories across months and years, not only episodes.

A unifying thread in this review is time. Type IV programmes wire data and deploy analytics, but they mostly observe snapshots. Type V systems treat *trajectories*—frailty progression, care-dependency transitions, cognitive decline—as first-class objects. This shift changes both engineering and evaluation. Engineering priorities move from static dashboards to pipelines that detect drift, refresh models, and log provenance as populations and practices evolve. Evaluation moves from one-off accuracy to learning-cycle KPIs that are explicitly temporal: time from drift detection to validated redeployment; stability of recommendations across updates; sustained narrowing of fairness gaps; and, critically, lead-time gained before deterioration. The test of an integrated, intelligent model is whether it consistently bends trajectories towards better function and fewer crises.

Clinically, risk stratification and pathway optimisation reduce preventable deterioration and streamline team work. Organisationally, success hinges on governance, interoperability, and model stewardship. EHDS and GDPR foreground citizen rights and trustworthy reuse; within ICMs this implies accountable data stewardship, validation, and bias monitoring. Co-design with clinicians and patients is non-negotiable. So are incentives that reward prevention and longitudinal outcomes rather than volume.

Beyond routine EHRs, richer multimodalities are moving into scope for integrated care. Polygenic risk scores, multi-omics, and imaging biomarkers can complement clinical and behavioural signals to refine risk stratification and personalise prevention, provided they are interpreted within fair and transparent frameworks [87–89]. Operationally, cross-sector collaborations and government-academic data partnerships proved their worth in crises and should be institutionalised for routine improvement [85]. On the engineering side, dynamic embeddings and zero-shot sequence models show promise for generalising across institutions and tasks, but require strong governance to manage drift and explainability [90,91].

Ethically, AI can both support and undermine equity. Bias in training data, opaque models, and uneven access can widen gaps. Explainability, fairness audits, and privacy-preserving learning help; legitimacy ultimately rests on participation—citizens having a meaningful say in how data and algorithms shape their care. Equity itself has a temporal dimension: we should expect not only parity at a timepoint, but convergence of trajectories across groups when mitigation is working.

Evidence remains uneven. Many studies are pilots, with short follow-up and narrow metrics. Comparative, longitudinal evaluations and cost-effectiveness are scarce, especially in low- and middle-

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income countries (LMICs). Future work should use open-science practices and reporting standards (e.g., Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis, Artificial Intelligence (TRIPOD-AI) [92]; Developmental and Exploratory Clinical Investigation of Decision-support systems driven by Artificial Intelligence (DECIDE-AI) [93]), and prioritise pragmatic, multi-site studies that assess clinical, economic, equity, implementation, and workforce effects together. Crucially, studies should report temporal endpoints, lead-time to detection, durability of effect after model updates, and the resource required to maintain learning cycles. Dashboards age. Good studies measure how fast and what it takes to keep them honest.

8. Future Directions

ICMs and AI are moving towards more adaptive ecosystems. Several priorities are now clear: trustworthy and explainable (increasingly causal) AI to support accountable decisions; federated, privacy-preserving analytics for cross-institution collaboration; real-time data streams from wearables, home sensors, and community sources to enable adaptive, closed-loop pathways; evaluation that values outcomes, experience, equity, and cost over accuracy alone; interoperable data spaces and shared ontologies (EHDS, Trusted Exchange Framework and Common Agreement (TEFCA) [94]) to stabilise semantics and governance; human–AI teaming with user experience (UX) and training that make the partnership usable in practice; explicit learning-cycle KPIs (latency from drift to redeployment, explainability compliance, fairness gap, and model provenance); and workforce upskilling and co-design capacity so clinicians, data scientists, and citizens can shape solutions together. Together, these priorities place integration within a longer-term model of coordinated human and machine decision support.

Three pragmatic priorities emerge. First, invest in longitudinal data assets and semantics: trajectory-aware phenotypes (frailty, care-dependency, cognition) and harmonised coding unlock earlier, fairer intervention. Second, standardise stewardship: monitor drift, refresh models, and report explainability and fairness routinely, not episodically. Third, align incentives to longitudinal value: use outcome-based contracts and shared-savings models that reward prevention and sustained equity improvement. Technically, continue advancing multimodal fusion and federated learning for privacy-preserving scale; clinically, expand trials that evaluate impact on admissions, function, and experience; organisationally, develop repeatable playbooks for government–academic–provider data collaboratives [51,60,85].

9. Conclusions

Intelligent integrated care moves service delivery closer to learning systems organised around people, data, and longitudinal outcomes. Realising this promise means pairing technical progress with governance and participation so that models are safe, fair, and trusted. Integration must span providers, infrastructures, regulation, and citizen stewardship, with incentives aligned to prevention and longitudinal outcomes. When implemented with strong governance, AI can strengthen coordination, improve outcomes and experience, and support equity and sustainability. Poorly governed deployment risks reinforcing fragmentation, bias, and distrust. Progress therefore depends on co-design, rigorous evaluation, transparent governance, and workforce development.

Current programmes in digital primary care, integrated home care, patient-centred medical homes, rural cardiovascular management, and older-adult support show that the field is advancing, but mostly through context-specific Type IV configurations rather than mature Type V learning systems [21,29–33]. Early 2026 evidence strengthens this reading rather than overturning it. The field is adding stronger building blocks, transdisciplinary ageing frames, multimodal precision-health models, transitional-care orchestration, privacy-preserving architectures, and leadership-focused governance thinking, but these still mostly appear as partial Type V components rather than mature, governed learning ecosystems [6,52,53,71,77,81,86]. The next step is not simply to add more algorithms. It is to pair longitudinal multimodal data with governed feedback loops, explicit model stewardship,

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and organisational arrangements that allow teams to learn safely over time. Under those conditions, integrated care can evolve from better-connected services into accountable learning systems for ageing populations and chronic disease management.

Supplementary Materials: The following supporting information can be downloaded at: Preprints.org. Section S1: Supplementary Methods (search strategy, databases, deduplication, screening workflow, eligibility criteria, appraisal, data extraction, and taxonomy-coding logic) with Figure S1: PRISMA-style audit trail of the search and selection process, and six extended-AI subsections supporting Section 4 of the main manuscript. Section S2: Taxonomy of Integrated Care Models (extended), including Table S1: Full Type I–V taxonomy of Integrated Care Models. Section S3: Supplementary policy frameworks beyond the three anchor frameworks referenced in the Introduction.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
API	Application Programming Interface
AUC	Area Under the ROC Curve
CCM	Chronic Care Model
CDS	Clinical Decision Support
DECIDE-AI	Developmental and Exploratory Clinical Investigation of Decision-support systems driven by Artificial Intelligence
DL	Deep Learning
ED	Emergency Department
EHR	Electronic Health Record
EHDS	European Health Data Space
FHIR	Fast Healthcare Interoperability Resources
GDPR	General Data Protection Regulation
HTA	Health Technology Assessment

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ICM	Integrated Care Model
IPCHS	Integrated, People-Centred Health Services
KPI	Key Performance Indicator
LMIC	Low- and Middle-Income Country
MDT	Multidisciplinary Team
NCD	Non-Communicable Disease
NLP	Natural Language Processing
NHS	National Health Service
OECD	Organisation for Economic Co-operation and Development
PREM	Patient-Reported Experience Measure
PROM	Patient-Reported Outcome Measure
SHAP	SHapley Additive exPlanations
SNOMED CT	Systematized Nomenclature of Medicine Clinical Terms
TEFCA	Trusted Exchange Framework and Common Agreement
TRIPOD-AI	Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis, Artificial Intelligence
UX	User Experience
WHO	World Health Organization

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