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From Connected Devices to Intelligent Care: Integrating Medical Devices, Digital Health, Functional Precision Oncology, and Global Healthcare Delivery

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Abstract

Healthcare innovation has advanced rapidly, yet care delivery remains fragmented across devices, information systems, laboratories, clinicians, and sites of care. This fragmentation limits the clinical and economic value of otherwise powerful technologies. This perspective argues that the next phase of healthcare innovation should move beyond simple connectivity toward closed-loop care: systems in which patient-generated and clinical data inform decisions, decisions trigger appropriate action, and outcomes continuously update the system. Medical devices can become sensing and therapeutic nodes; interoperable information technology can become a layer of predictive intelligence; and emerging approaches such as digital twins and functional precision oncology can extend the model from monitoring to simulation and individualized treatment selection. Chronic wound care provides a practical example in which integration can be evaluated through measurable outcomes such as healing, hospital utilization, readmissions, amputations, and total episode cost. Functional cancer testing provides a second example, complementing molecular profiling by measuring *ex vivo* response in living patient-derived tumor material. Globally, resource-constrained environments may accelerate mobile-first, decentralized models that can later inform higher-cost health systems. However, interoperability alone is insufficient. Clinical adoption will depend on evidence, human oversight, privacy, transparency, explainability, validation, and trust. The central proposition is that healthcare's next competitive and clinical advantage will come not from isolated products, but from integrated systems that convert data into timely, accountable action.

Keywords: medical devices; digital health; interoperability; closed-loop care; digital twins; functional precision medicine; oncology; wound care; artificial intelligence; global health

Introduction: Fragmentation Is a Clinical Risk

Consider a recovering cardiac patient at home using a wearable rhythm monitor, a blood-pressure cuff, a glucose sensor, a medication application, and a home-health reporting platform. The technology may be sophisticated, yet if each system creates a separate stream of information, the cardiologist, primary-care physician, home-health team, and patient can still be working from different versions of reality. A deterioration that is visible across the combined data may remain invisible within any single silo.

This is the paradox of contemporary healthcare: innovation is abundant, but coordination is scarce. In the United States, national health expenditures reached \$5.3 trillion in 2024, or 18.0% of gross domestic product [1]. At this scale, the question is no longer whether healthcare can generate more data. It is whether health systems can turn data into decisions and decisions into better outcomes without adding unacceptable cost or complexity.

The World Health Organization's current digital-health strategy similarly treats digital transformation as a health-system problem rather than a software problem, emphasizing

integration of financial, organizational, human, and technological resources [2]. The implication is important: a device, algorithm, laboratory assay, or electronic record has limited value when deployed as an isolated endpoint. The unit of innovation should increasingly be the care pathway.

From Connectivity to Closed-Loop Care

Connectivity is necessary, but it is not the destination. A connected system can transmit data while leaving clinicians responsible for interpreting every signal, deciding what matters, and manually initiating the next step. A closed-loop model is more ambitious: data are captured, interpreted in context, translated into a decision, linked to an appropriate action, and then reassessed through feedback.

A useful conceptual sequence is: Data → Decision → Action → Feedback. The degree of automation should vary with clinical risk. In some settings the system may simply prioritize a clinician alert; in others it may safely adjust a device within validated parameters while maintaining human oversight. The objective is not to remove clinicians from care. It is to reserve human attention for decisions that genuinely require judgment. Consider wound care. A future smart dressing or sensor-

enabled negative-pressure system might detect clinically relevant changes, combine them with wound images and patient-level risk factors, recommend or implement a protocol-defined adjustment, and escalate to the clinician when thresholds are crossed. Such a system would move beyond remote monitoring toward active management. Importantly, examples of autonomous adjustment should be treated as a design direction rather than a claim that every such function is presently validated or authorized.

Health IT as Predictive Intelligence

Health information technology has traditionally served as a repository and communication layer. Its next role is potentially more consequential: integrating longitudinal, multimodal data to anticipate trajectories and support decisions before deterioration becomes obvious.

Digital twins illustrate both the promise and the need for restraint. In healthcare, a true digital twin is generally understood as a patient-specific virtual representation that is dynamically updated and has predictive or decision-support capability. A 2025 scoping review found that only 18 of 149 studies using digital-twin terminology fully met stringent criteria for personalization, dynamic updating, and decision support [3]. The term therefore should not become shorthand for every predictive model.

Properly validated, digital twins could enable clinicians to simulate alternative treatment pathways, estimate likely trajectories, and update recommendations as new information arrives. Yet verification, validation, and uncertainty quantification are essential if such models are to support clinical decisions [4]. The conceptual progression is therefore not simply retrospective analytics to prediction, but reaction → prediction → simulation → optimization, with evidence and human accountability at each step.

Integrated Care Pathways: Measure What Matters

Integration should be judged by clinical and operational outcomes, not by the number of connected endpoints. Chronic wound care is a useful proving ground because the pathway crosses settings, requires repeated assessment, and can culminate in hospitalization, infection, surgery, or amputation when care fails.

An integrated wound-care program can combine advanced therapies, standardized imaging, device-generated data, remote follow-up, and escalation protocols. The appropriate business and clinical case should be built prospectively around measurable endpoints: time to healing, hospital length of stay when hospitalization occurs, 30-day readmission, infection-related utilization, amputation, clinician time, adherence, and total cost per episode. Rather than promising a predetermined percentage improvement, organizations should establish a baseline and measure the incremental effect of the integrated pathway.

This framework also creates a disciplined test for investment. Technology that produces more data but does not improve

a defined outcome may be interesting; technology that measurably changes the pathway can be valuable.

Functional Precision Oncology: From Molecular Probability to Observed Response

Oncology provides a compelling extension of the same integration thesis. Genomic profiling has transformed cancer classification and treatment selection, but genotype does not always predict phenotype or drug response. Functional precision medicine seeks to complement molecular information by exposing living patient-derived tumor material to therapies *ex vivo* and measuring response.

A 2025 review described a broader shift toward functional precision medicine in which living patient tumors or patient-derived models are directly treated *ex vivo* to help predict patient-specific therapeutic response [5]. Prospective evidence is emerging. In the SMARTRial of hematologic malignancies, *ex vivo* drug-response reports were delivered within seven days for 91% of 80 participants, and *ex vivo* chemotherapy resistance was associated with treatment failure; predictive findings were also evaluated in a separate validation cohort [6]. These results support feasibility and potential clinical value, but they do not establish universal utility across tumor types.

The strongest future model is therefore complementary rather than competitive: molecular profiling identifies biologic targets and mechanisms; functional testing measures observed response under laboratory conditions; clinical information defines feasibility and patient context; and longitudinal outcome data feed back into the decision system. In solid tumors, including pancreatic cancer, this remains an active area of research and requires tumor-specific prospective validation before routine clinical claims can be made.

Integrated with secure informatics, functional testing could eventually become one layer of an oncology ‘learning system’ in which molecular features, *ex vivo* response, treatment selection, toxicity, imaging, and outcomes continually refine future recommendations. This is also a natural bridge between functional testing and the longer-term digital-twin concept in oncology [7].

Global Delivery and Reverse Innovation

The integration challenge is global, but the optimal architecture will not be identical everywhere. Resource-constrained health systems often have fewer legacy platforms to bypass. That can create an opportunity to move directly toward mobile-first workflows, portable diagnostics, cloud-based specialist support, and decentralized monitoring.

This is a form of reverse innovation: solutions designed under constraints can reveal simpler and less expensive ways to organize care, and those lessons can flow back to high-income systems burdened by complexity. WHO’s digital-health work explicitly emphasizes interoperability, data sharing, governance, and solutions that can be used across Member States with differing levels of digital capacity [2,8].

The principle is not that low-resource settings should receive less sophisticated medicine. It is that sophistication should be concentrated in the intelligence of the system rather than in unnecessary infrastructure. A portable device connected to a well-designed clinical network may create more access than an advanced device that depends on a tertiary center.

Trust, Ethics, and the Human-in-the-Loop

The technical architecture is only one layer of adoption. Trust is another. Clinicians need to understand when a recommendation is reliable, what data informed it, and when they should override it. Patients need meaningful information about how their data are collected, used, protected, and shared. FDA transparency principles for machine-learning-enabled medical devices emphasize clear communication of intended use, performance, logic when appropriate, limitations, and information needed by users to make safe decisions [9]. FDA also identifies explainability as a way to address the opacity of some AI systems and safely augment human decision-making [10]. WHO governance work similarly highlights ethical use, privacy, security, safety, cost-effectiveness, and sustainability [11].

For high-stakes care, ‘closed loop’ must not become synonymous with ‘unaccountable automation.’ A responsible system defines the human role, the evidence threshold for automated action, escalation rules, auditability, cybersecurity requirements, and

ongoing performance monitoring. Trust should be engineered into the system, not added after deployment.

A Platform Model for Healthcare Innovation

The strategic implication is a shift from product thinking to platform thinking. A product performs a function. A platform coordinates functions across a pathway. Medical devices can supply sensing and therapy; software can integrate and interpret data; laboratories can contribute molecular and functional evidence; clinicians provide judgment; and delivery networks bring the system to the patient.

For a company such as Devon Medical Products, the opportunity is not to claim ownership of every layer, but to design products and partnerships so that the layers can work together. Wound care can serve as an initial use case because outcomes are observable and workflows are repeatable. Functional precision oncology can represent a more advanced use case in which laboratory testing, molecular data, clinical judgment, and longitudinal outcomes converge.

From an investment perspective, this architecture can support multiple economic models—devices, consumables, software or analytics, services, and strategic partnerships—but recurring revenue is not itself evidence of clinical value. Sustainable enterprise value will depend on demonstrating that integration produces outcomes that matter to patients, clinicians, health systems, and payers.

A Practical Roadmap

Layer	Core Question	Example Measure	Governance Requirement
Clinical	Does the pathway improve care?	Healing, readmission, treatment response	Clinical oversight and protocol
Operational	Does it reduce friction?	Time to intervention, clinician workload	Workflow design and escalation
Economic	Does it create net value?	Total episode cost, avoidable utilization	Transparent cost accounting
Data	Can information move and be understood?	Interoperability, completeness, latency	Standards, security, consent
AI / Modeling	Are predictions reliable?	Calibration, validation, uncertainty	Explainability, monitoring, human override
Global Scale	Can the model work in different settings?	Access, affordability, uptime	Local adaptation and equity

Conclusion

The next phase of healthcare innovation will not be defined by a single device, algorithm, laboratory assay, or delivery channel. It will be defined by how effectively these capabilities are integrated around a patient and a measurable clinical objective. The progression is clear: connected devices can become closed-loop care systems; information technology can evolve from documentation toward predictive intelligence; digital twins may eventually support simulation and optimization; functional precision oncology can add observed biological response to molecular probability; and global, decentralized models can expand access while teaching high-cost systems how to simplify.

But integration without evidence can amplify error just as easily as it amplifies value. The systems most likely to earn clinical trust and scale responsibly will be those that are interoperable, measurable, transparent, validated, secure, and designed around human judgment. The future is not simply more technology. It is coordinated intelligence translated into timely action.

Declarations

Conflict of Interest

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Patient Consent

The opening patient scenario is illustrative and composite; it is not presented as an identifiable clinical case.

Article Type

Perspective / Viewpoint. This manuscript does not report a clinical trial or original patient-level research.

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