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Barriers to translating continuous monitoring technologies for preventative medicine

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While treatment remains essential, disease prevention often proves more effective in improving outcomes, enhancing well-being and reducing healthcare costs. Despite this understanding, preventative medical practices are still underutilized. Continuous monitoring technologies can help to address this gap by enabling early symptom detection, tracking disease recurrence and assessing treatment responses, yet few of the technologies have been integrated into clinical practice. In this Review, we discuss notable advances in continuous monitoring and the barriers to their translation. We focus on technologies that enable either continuous measurement for at least one week or periodic measurements for at least one month, including remotely interfacing technologies, wearables and other directly interfacing systems, and internally interfacing implanted devices. Continuous monitoring improves disease-risk assessment, tracks disease progression and enhances overall health management. However, broader and more reliable datasets from diverse clinical trials, alongside supportive policies and financial incentives, will be essential to overcoming translational barriers and to integrating these technologies into healthcare.

Preventative medicine focuses on early disease detection and on the monitoring of pre-disease or early-stage conditions to prevent or limit progression. Preventative medicine can improve the outcomes for chronic diseases such as diabetes, uraemia and congestive heart failure. In the USA, more than 37 million people have diabetes, with one in five remaining undiagnosed[1]. Although diabetes symptoms can be subtle, early detection reduces the risk of complications[2]. Similarly, an estimated 8 million Americans have uraemia[3], a condition with equally elusive symptoms, yet early detection can slow disease progression and reduce morbidity[4]. Hospitalizations due to congestive heart failure in the USA exceed 1 million annually, with two-thirds resulting from fluid retention. Many of these cases of hospitalizations could be prevented through preventative monitoring, early detection and diuretic management[5]. Preventing disease and managing symptoms before they worsen is more effective than treatment and hospitalization, particularly for chronic conditions[6,7].

Despite awareness of preventative care, only about 8% of adults in the USA receive adequate preventative services[8]. The primary barrier

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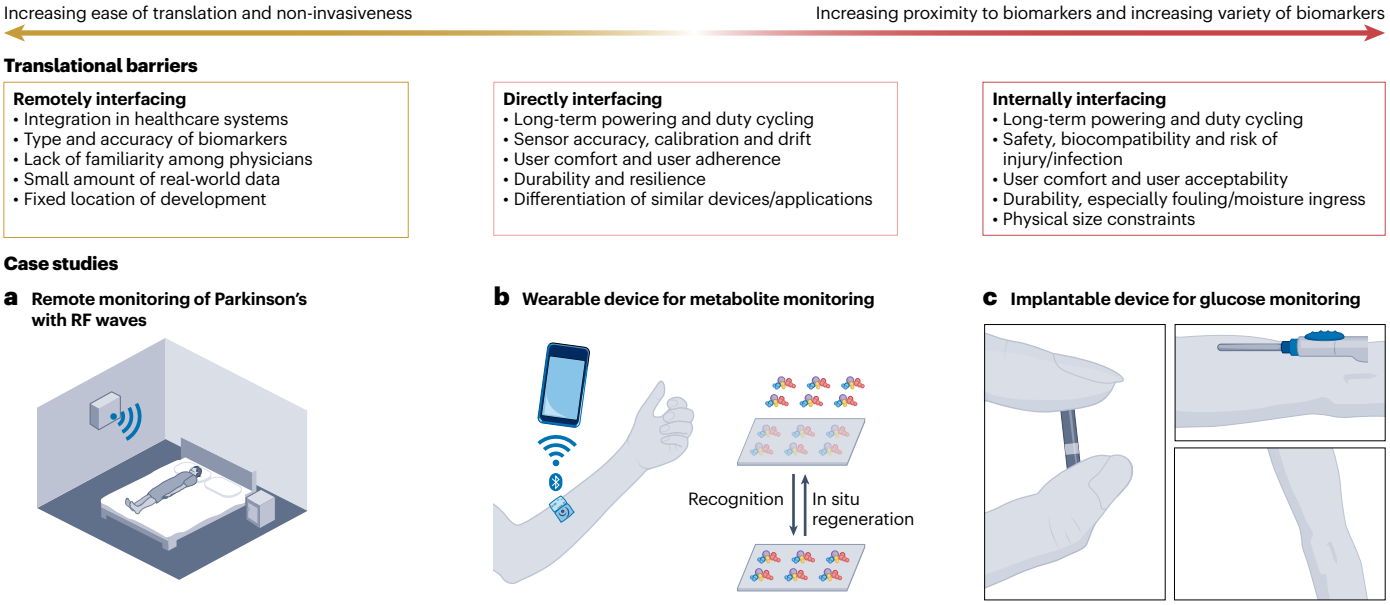

Fig. 1 | Translational barriers of continuous monitoring technologies for preventative medicine. The technologies can remotely, directly or internally interface with the human body to monitor diagnostic signals, biomarkers or analytes. **a**–**c**, The three technologies highlighted—remote monitoring of Parkinson's disease with RF waves (**a**), a wearable device for metabolite monitoring (**b**) and an implantable device for glucose monitoring (**c**)—correspond to the case studies in Boxes 1–3. Panel **a** adapted from ref. 28 under a Creative Commons license CC BY 4.0. Panel **b** adapted from ref. 171, Springer Nature Limited.

is financial misalignment: healthcare systems are largely funded for treatment of diseases and their exacerbations, not methods for their prevention[9]. As a result, medical research focuses on treatments and cures rather than early intervention[10], and insurance covers treatments while excluding preventative measures owing to a perceived low value[11].

In the USA, the percentage of adults aged 35 years and older receiving adequate preventative services decreased from 9% in 2015 to 5% in 2022 (ref. 12). Medical technologies for continuous monitoring may help to bridge this gap by improving access and enabling early detection without increasing clinical workload. These technologies can identify preclinical signs of disease and detect symptom escalation, particularly for conditions such as diabetes[13] and uraemia[14]. They are most relevant for secondary prevention, whereby early disease detection allows timely intervention, and for tertiary prevention, whereby monitoring chronic conditions reduces complications. Current monitoring technologies operate across scales, from individual-level sensors to population-wide informatics. However, most fail to transition from early prototypes to widespread commercial adoption[15].

This Review focuses on continuous monitoring technologies allowing for at least 1 week of uninterrupted use or of periodic monitoring for at least 1 month. We classify the technologies by their interface with the body—internally interfacing, directly interfacing and remotely interfacing—as these categories share similar regulatory and translational challenges, and examine key barriers to their translation (Fig. 1).

Remotely interfacing technologies

Remotely interfacing technologies enable continuous monitoring without direct patient contact, providing non-invasive, safe and convenient options for patients and clinicians. These technologies span several categories (Fig. 2), differing in their underlying mechanisms and monitoring objectives. Informatics, which use either individual-level electronic health records (EHRs) or population-level wastewater data, show promise for tracking disease risk and progression. They gained initial traction during the COVID-19 pandemic, when they helped to direct resources and investments towards monitoring virus transmission (through waste water) and assessing the pandemic's impact on population health (through EHRs)[16–21]. However, translational challenges remain, particularly for EHR-based approaches, as they often rely on machine-learning models that reduce transparency and may limit physician acceptance.

Researchers have also explored video-based health monitoring. Previous research has demonstrated the feasibility of extracting heart rate from subtle variations in facial skin colour and extracting respiratory rate from slight body movements. However, these systems remain sensitive to lighting and environmental variations, limiting real-world application. Robotics have been deployed as mobile platforms for computer vision systems: in one example, a quadruped robot mounted with RGB and infrared cameras as well as a teleconferencing system was used for patient triage during the COVID-19 pandemic[22]. However, cost is a considerable translational barrier for scalable, real-world deployment.

More recently, off-body sensors have been designed to leverage environmental radio waves for the monitoring of vital signs[23], motor symptoms[24], sleep stages[25,26] and medication adherence[27]. These devices passively collect physiological signals in the background while patients go about their daily activities, making them well suited for long-term monitoring. Some have already been deployed in pharmaceutical clinical trials to track disease progression[24,28–30] and to assess treatment outcomes, with early translational success[31–35]. Beyond pharmaceutical applications, off-body sensors hold potential for clinical care, particularly in chronic disease management. However, widespread adoption will require further evidence linking their measurements to actionable clinical decisions, along with insurance coverage. As with EHR-based informatics, devices' reliance on machine learning may also affect physician confidence.

Telehealth is another category of remotely interfacing technologies. By incorporating remote sensors (such as weight scales) and contact-based devices (such as blood-pressure cuffs), telehealth enables the remote exchange of clinical information through video interfaces. By providing clinicians with diagnostic and therapeutic data, telehealth enhances patient care through improved accessibility, convenience and cost-efficiency while overcoming geographical barriers.

Population informatics

Wastewater analysis for continuous or periodic monitoring has seen substantial translational success in recent years. In the USA, the COVID-19

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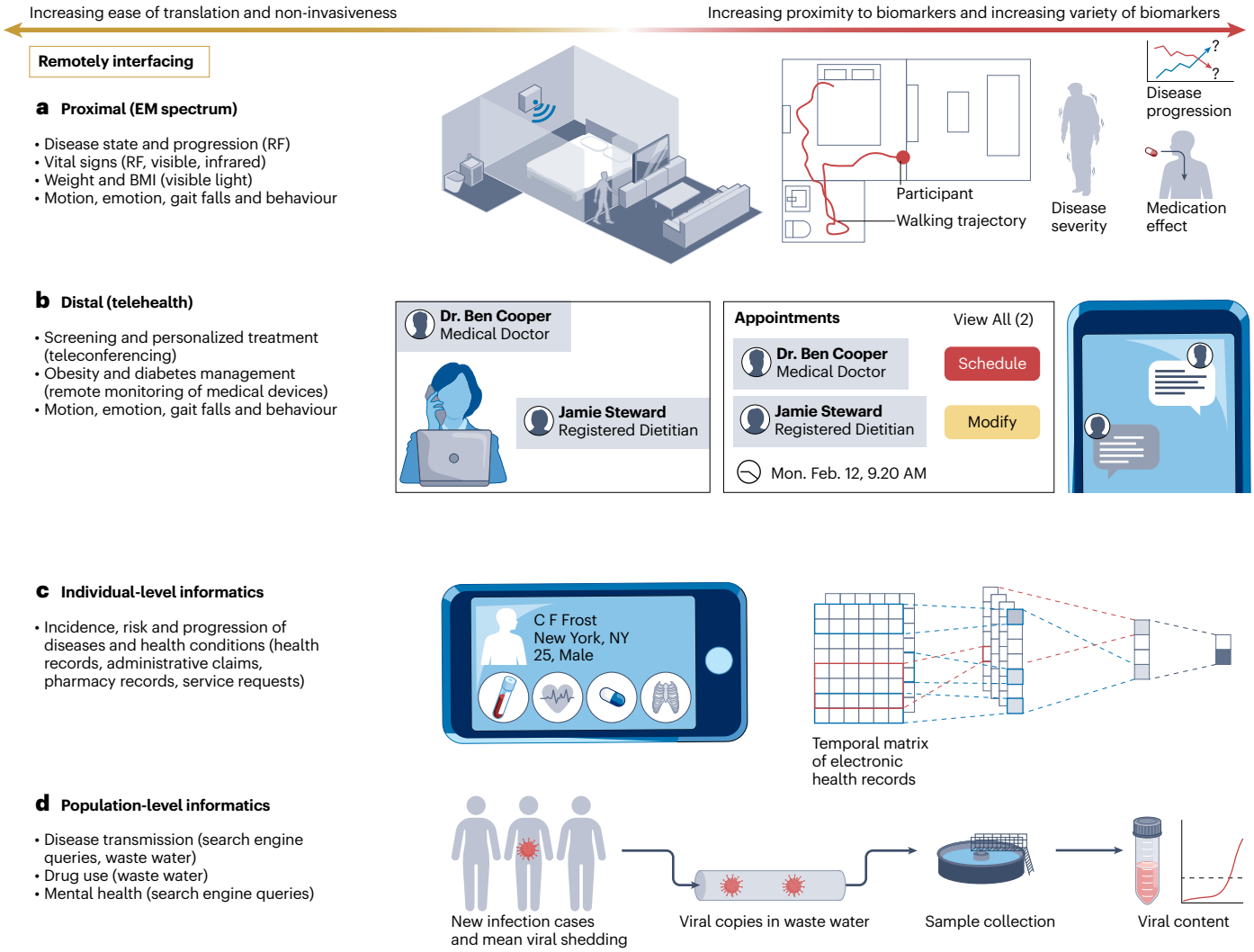

Fig. 2 | Modalities of continuous monitoring for remotely interfacing technologies. Patient informatics, population informatics through wastewater epidemiology, telehealth and the computational analysis of electromagnetic (EM) spectral data enable convenient, contactless and remote monitoring. **a**, Monitoring the severity and progression of Parkinson's disease using radio waves. **b**, Telehealth program for blood-pressure monitoring and hypertension. **c**, Study of concordance between telehealth and in-person diagnosis. **d**, Use of deep learning and EHRs for disease prediction, such as in the prediction of SARS-CoV-2 infection through the concentration of SARS-CoV-2 RNA in waste water. Data in **c** from ref. 84, and data in **c** and **d** from ref. 55. Images adapted with permission from: **a**, ref. 24, AAAS; **d**, ref. 39, Elsevier.

pandemic spurred interest in using waste water to forecast disease transmission[36]. Since 2020, daily samples have been collected in Massachusetts[16], demonstrating the feasibility of long-term population monitoring. Wastewater networks have previously served as biosensors for disease prevalence and substance use, but most studies have been limited to individual treatment plants. Expanding biosensing to include intermittent sampling from both treatment plants and downstream sites, such as sewer manholes, allows for adjusting resolution and sampling catchment areas to target public health priorities. Ideal wastewater biomarkers include pathogens excreted renally or faecally. Xenobiotics can also be detected, provided that they undergo renal or hepatic metabolism. A recent innovation—detecting glucuronidated xenobiotic metabolites—has further improved precision by ensuring that measurements reflect human use[37].

During the pandemic, wastewater-based epidemiology proved to be a highly cost-effective tool for monitoring disease transmission, allowing policymakers to prepare health systems ahead of infection surges[17,18,38]. Multiple studies showed that SARS-CoV-2 RNA-fragment concentrations could predict hospital presentations several days in advance[39,40]. These insights may also inform public-health measures for high-risk populations and settings[41,42]. Beyond infectious-disease monitoring, wastewater analysis has been used to estimate substance-abuse prevalence[43–45]. By measuring glucuronidated drug metabolites in wastewater, these systems provide indicators of human consumption. Maps from geographical information systems overlaid on wastewater drug-concentration data enable longitudinal biosensing, and have revealed patterns of drug use, the emergence of new substances and the effectiveness of public-health interventions[46,47].

The translation of COVID-19 wastewater epidemiology was rapid; funding from the American Rescue Plan Act repurposed an existing foodborne pathogen-surveillance network to sequence wastewater samples[48]. However, this swift adoption was driven entirely by the urgency of the pandemic. To build on these lessons, the United States Centers for Disease Control and Prevention (CDC) established the National Wastewater Surveillance System to develop infrastructure for monitoring emerging pathogens[49]. Today, wastewater analytics in the USA continue to track seasonal pathogens, emerging diseases (such as monkeypox) and drug use. In Europe, the European Monitoring Centre for Drugs and Drug Addiction funds wastewater monitoring across major cities to track substance use trends[50]. Before the

pandemic, several barriers limited the translation of wastewater epidemiology. Effective systems must not only identify robust analytical targets but also account for bacterial degradation. They also require high-resolution detection at large volumes to enable continuous monitoring. Moreover, monitoring sensitive substances or pathogens raises bioethical concerns that must be addressed before implementation.

Patient informatics

Data mining of search-engine queries is another approach to population-level monitoring. It uses correlations between infectious-disease incidence and topical internet-search terms. This method has successfully been used to predict the spread of Coxsackie virus[51], influenza[52] and SARS-CoV-2 (ref. 53). During the COVID-19 pandemic, it was also applied to mental-health-related searches to track anxiety symptoms and mental-health trends[54]. Combining search-engine data mining with machine learning can further improve prediction accuracy[53].

At the individual level, analyses of EHRs enable continuous monitoring of disease incidence and risk. As health records are updated, machine-learning models can process large datasets to identify health trends. EHRs have been used to monitor disease incidence[55], to assess osteoporotic fracture risk[19,21] and to classify patients according to diabetes type and subtype[20,56]. Other applications include using administrative claims, pharmacy records, service requests and laboratory results to track health conditions and diabetes risk[57–59]. In clinical settings, EHR-based models have supplemented inpatient monitoring to predict sepsis risk and mortality from it[60]. However, a key limitation of EHR analysis is the absence of social determinants of health, which are critical for translational informatics[61]. As a result, conclusions drawn from EHR data may be incomplete.

The primary translational barrier to applying machine learning to EHRs is generalizability: a model may perform well on the data it was trained on but may not reliably extend to broader populations[62]. One challenge is racial and ethnic bias. The use of commercial medical-informatics algorithms—including those already in clinical use—can lead to systematic biases against minority populations[63]. Other models perform less accurately in under-resourced populations, potentially exacerbating healthcare disparities[64]. A related challenge is model calibration, which ensures that predicted probabilities correspond to true event frequencies. Recent studies have proposed methods to improve calibration, enhancing the interpretability of model outputs[65,66].

Another major challenge is EHR interoperability. Formats vary widely, and datasets contain thousands of potential predictors. In the USA, policies such as the Trusted Exchange Framework and Common Agreement have established technical networks for EHR data exchange, whereas the United States Core Data for Interoperability standardizes data elements. However, stringent regulations and limited stakeholder cooperation continue to hinder interoperability. Even more fundamental is the issue of EHR adoption. Despite the benefits of EHRs, financial misalignment remains a major barrier: physicians must cover the costs of outpatient EHR systems, yet the primary financial beneficiaries are EHR vendors[67,68]. As a result, many clinicians remain reluctant to use EHRs, limiting their potential for continuous monitoring.

Telehealth

Telehealth enables healthcare delivery through digital technologies and telecommunications, allowing patients to consult clinicians virtually, and clinicians to access electronic information remotely. Telehealth offers convenience, and can integrate with wearable or portable devices to capture physiological data at a volume or frequency that is unfeasible for in-person visits.

Continuous monitoring through telehealth requires a virtual care team to regularly track clinically relevant physiological signals or biomarkers. For example, Form Health, a telehealth company focused on obesity management, uses digital scales to transmit weight data from patients to an external care team for virtual clinical recommendations. Teladoc, which offers a broad range of continuous monitoring services, enables patients to track health metrics, such as blood glucose (for diabetes management), blood pressure (for hypertension) and weight. These data can inform virtual consultations or trigger digital interventions if abnormalities are detected. A key enabler of the success of Form Health and Teladoc is their eligibility for insurance coverage in the USA. However, although Teladoc may increase access to healthcare for patients by not requiring in-person providers[69], its users do not disproportionately come from underserved communities[70].

Telehealth extends beyond monitoring and screening. The rapid collection and transmission of data can further enable pre-emptive and intensive care. For example, many people with hypertension fail to reach treatment goals that minimize cardiovascular risk[71,72]. Traditional in-person care limits treatment adjustments to in-person visits every 3–6 months, restricting opportunities for timely intervention. By contrast, telehealth allows for continuous blood-pressure monitoring, substantially increasing the frequency of treatment adjustments. Evidence of hypertension control from clinical trials supports the effectiveness of remote blood-pressure monitoring[73–75]. Another advantage of telehealth is its capacity for personalization and precision[76]. For example, continuous glucose monitoring allows for the transmission of real-time data to patients, family members and clinicians, and can therefore enable improvements in glycaemic control and diabetes-related quality-of-life measures[77].

Telehealth has been shown to enhance care quality and cost efficiency while maintaining high patient and clinician satisfaction[78–80]. Remote data transmission to external care teams is gaining acceptance, with regulatory standards expanding medical-billing permissions for telehealth services[81]. Adoption surged during the COVID-19 pandemic[82], but substantial translational barriers remain. Privacy and security concerns arise from the inclusion of personal identifiers in digital health data[83]. Most telehealth services operate independently of health system networks, and therefore require further integration to facilitate seamless clinical use across providers. Although studies indicate that telehealth diagnoses can match in-person accuracy[84], the digital medium has limitations—for example, wireless bandwidth affects the reliability of fine-motor assessments, potentially leading to misdiagnoses[85] and, although some healthcare systems use telehealth to reach remote or rural populations, others resist its adoption because reimbursement rates are lower than for in-person care[86].

Computational analysis of camera data

Video data contain diagnostically relevant signals that can be measured remotely. The most well-known application is remote photoplethysmography (rPPG), which uses RGB cameras to detect changes in skin reflectance. These changes correlate with capillary dilation and constriction, enabling estimation of vital signs such as heart rate, respiratory rate, blood-oxygen saturation and blood pressure[87]. rPPG allows for continuous and contactless monitoring, and has been tested in emergency rooms[88,89]. However, rPPG requires the individual to remain within the camera's field of view. To address this, robotic systems—such as ground robots[90], drones[91] and miniature robotic blimps[92]—can be used to track the individual and perform rPPG. The COVID-19 pandemic accelerated research into robotic vital-sign monitoring, but deployment remains costly and impractical at scale[93–95].

Computer-vision methods can also estimate weight and body mass index by detecting anatomical landmarks, analysing body contours, extracting features with deep learning and integrating these elements for prediction[96]. Less-accurate approaches use only facial images, relying on facial geometry or deep-learning models[97,98]. Other applications of RGB cameras include monitoring the discomfort of infants through facial expressions[99] and nasal-versus-mouth breathing analysis for sleep disorders[100]. RGBD cameras (that is, cameras that provide both colour and depth), can precisely track physical behaviour, including

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gait, limb movement and fall detection[89,101]. RGB cameras can also be used for colorimetric assays, enabling unconventional applications such as the periodic monitoring of excreta[102].

Despite their accessibility, visible light-capturing methods face challenges in accuracy and reliability. As they rely on light reflectance, variations in lighting and motion artefacts can affect performance[103]. Although there are strategies to mitigate motion artefacts[104], they remain condition dependent. Moreover, racial bias has been documented in computer-vision methods for continuous vital-sign monitoring, including state-of-the-art rPPG (ref. 105).

Infrared cameras enable the direct monitoring of skin temperature[63] and have been explored for applications such as respiratory rate[106,107], stress[108] and depression monitoring[109], although with lower accuracy than clinical gold standards. Infrared monitoring presents several challenges—all objects emit and reflect thermal radiation, introducing noise and reducing image texture. Moreover, infrared cameras are sensitive to factors such as skin tone and distance, requiring calibration against a blackbody[110]. To address these limitations, a recent machine-learning-based approach decluttered heat signals to recover thermal-image texture, therefore enabling large-scale temperature monitoring and potentially improving infrared-based diagnostics[111].

Overall, although camera-based health monitoring is inexpensive, safe and accessible, its accuracy and clinical use remain limited. Moreover, few diagnostically useful signals beyond vital signs have been identified. For example, camera-based approaches, which rely on visible and near-infrared light, cannot be used to measure blood-glucose levels[112].

Computational analysis of radio signals

Radiofrequency (RF) signals can be used to monitor respiratory signals[113,114], heart rate[115], sleep stages and apnoea[25,26], medication-administration errors[27], and movement and behavioural symptoms[24,29,30,116]. These sensors detect wireless signal reflectance, which varies with body motion, without requiring wearable devices. In contrast to monitoring in the visual or infrared spectra, RF-based monitoring does not require line of sight, enabling easy integration into home and clinical settings. The passive and contactless nature of this approach also enables longitudinal monitoring without burdening patients. Early research focused on remote patient monitoring, whereas more recent work has leveraged this type of measurements to develop disease-specific digital biomarkers. For example, wireless monitoring of nocturnal respiration combined with a neural network trained on clinical datasets has been used to detect the occurrence and severity of Parkinson's disease[28] (Box 1).

First-generation RF-based monitoring methods relied on signal processing, whereas more recent technologies use deep learning. A common challenge in RF-spectrum monitoring is entanglement: when multiple individuals are monitored in proximity, their signals interfere and overlap. To address this, RF-based sensors use waveform shaping through antenna arrays and frequency-modulated continuous wave technology to differentiate signals reflected from different individuals, which allows for continuous multi-individual monitoring[117]. These systems also apply independent component analysis to reduce residual interference and to accurately isolate individual signals, even when people are close together[23].

Certain RF-based technologies (such as Emerald);[23,26,118,119] have been validated (including third-party validation[120]) against gold-standard methods for measuring breathing and heart rate, gait speed, sleep hypnograms and apnoea. These systems have also been deployed to monitor patients with Parkinson's disease[24,28], Alzheimer's disease[29,30], amyotrophic lateral sclerosis[33], Crohn's disease, atopic dermatitis[35], endometriosis[121], Rett syndrome[34] and facioscapulohumeral muscular dystrophy[122]. Some of these technologies have been commercialized and are used by the biopharmaceutical industry in clinical trials to assess disease progression and therapeutic outcomes[31–33].

BOX 1

Remote monitoring of Parkinson's disease using RF signals

Parkinson's disease is a rapidly growing neurological disorder that remains difficult to diagnose. Imaging, blood tests and medical-history reviews can help to rule out alternative conditions, but no conclusive diagnostic test exists. The United States National Institutes of Health estimates that 1 million Americans have the disease, and that only 0.5 million are diagnosed[288]. New technologies for the continuous monitoring of individuals at risk of Parkinson's disease are needed to enable early diagnosis and track disease progression.

Remote monitoring using RF waves offers a fully non-invasive and convenient solution. A device emits radio waves and detects their reflection off human bodies. Signal-processing algorithms and neural networks can then be used to extract nocturnal breathing patterns and gait speed from the reflected signals. Statistically significant correlations between these metrics and Parkinson's disease severity and progression, as assessed by the Movement Disorder Society-Sponsored Revision of the Unified Parkinson's Disease Rating Scale, were reported.

Notably, gait speed was found to be more sensitive to the progression of Parkinson's disease than the rating scale, whereas nocturnal breathing led to statistical significance as a disease-progression marker even when the clinician score did not. This highlights a key advantage of remote continuous monitoring: an RF-emitting device can collect extensive longitudinal data, reducing noise and improving sensitivity, whereas frequent clinician-administered scoring is impractical.

These findings have motivated biotechnology companies developing therapies for Parkinson's disease to incorporate RF-based passive sensing into clinical trials to monitor disease progression and assess treatment outcomes[31,32]. However, further validation is needed. The gait-speed study involved a relatively small cohort (n=50), and therefore requires broader validation, whereas the nocturnal breathing study was externally validated on a dataset of 1,920 individuals yet requires population-wide generalization testing.

Although RF-based monitoring has shown early success in drug development, widespread adoption will require regulatory approval. Further, although the technology holds promise in clinical care, particularly for risk assessment and the early detection of exacerbations in chronic diseases, integrating RF-based monitoring into healthcare systems poses considerable challenges. Moreover, while physiological signals captured by at-home monitoring systems can serve as non-invasive surrogate markers for health conditions, they generally have lower sensitivity and specificity than clinical gold-standard methods. The key advantage of RF-based systems is their ability to provide continuous and unobtrusive monitoring, which is advantageous for early detection and may help to prevent symptom escalation. Yet healthcare systems remain largely reactive, prioritizing treatment over prevention. Moreover, insurance coverage for such monitoring is limited, with few exceptions for specific conditions.

Directly interfacing technologies

Wearable and portable devices have been developed to continuously monitor a variety of signals, analytes and biomarkers[123]. These technologies use diverse sensing mechanisms and form factors that directly interface with the human body, extracting biophysical,

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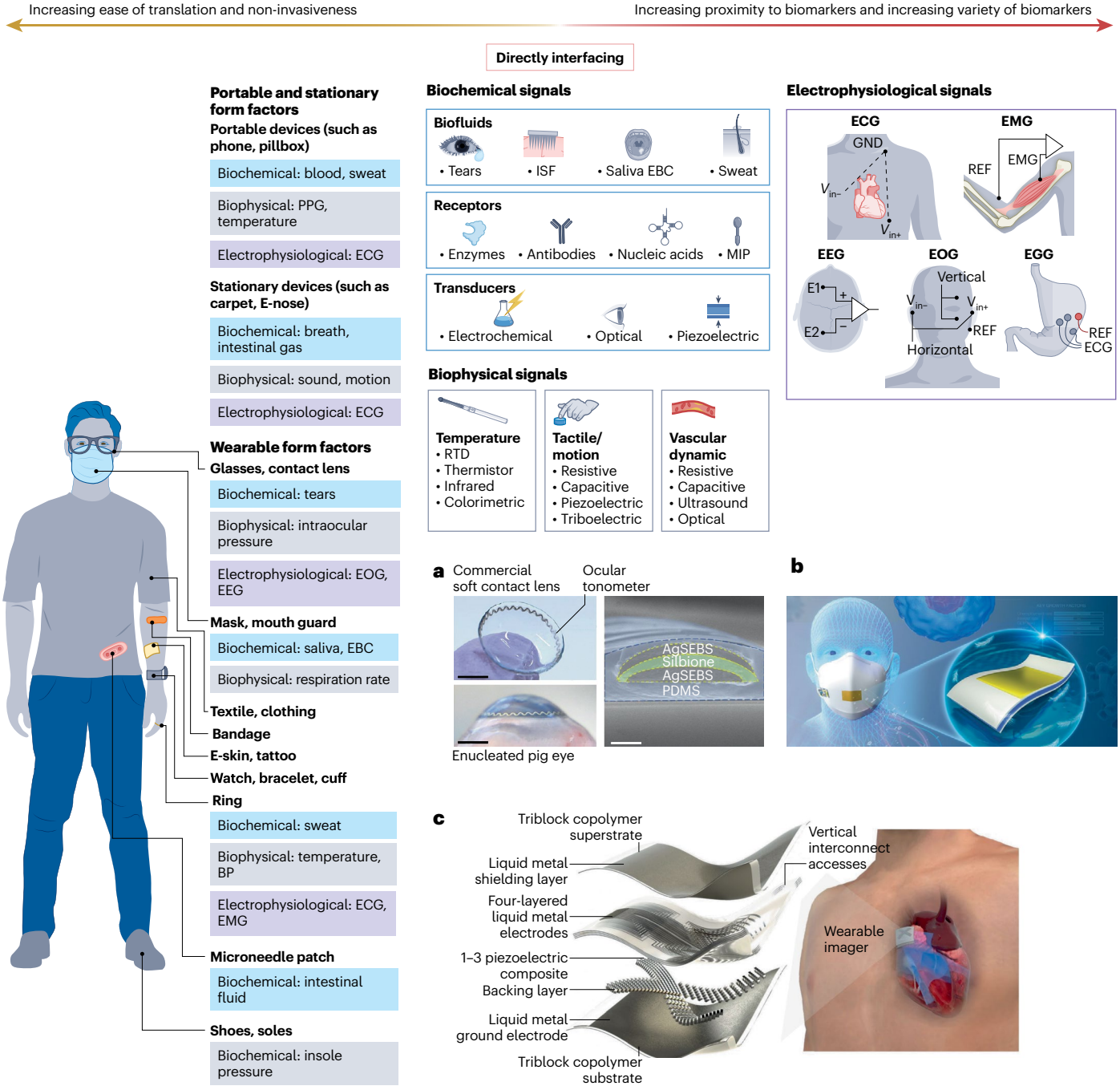

Fig. 3 | Extractable biosignals and sensing mechanisms of directly interfacing technologies. These technologies may be in the form of wearable or portable devices. **a**, Contact lenses for intraocular pressure monitoring, with potential applications in glaucoma monitoring. AgSEBS, composite of silver and styrene–ethylene–butylene–styrene; PDMS, polydimethylsiloxane. Scale bars, 5 mm (left) and 20 µm (right). **b**, Facemask for monitoring respiratory rate and respiratory conditions, including restrictive lung diseases. **c**, Wearable ultrasound device for imaging cardiac functions, with improved electromechanical coupling between the device and the chest. BP, blood pressure; EBC, exhaled breath condensate; E-nose, electronic nose; E-skin, electronic skin; GND, ground; ISF, interstitial fluid; REF, reference. E1 and E2 refer to electrodes. Images adapted with permission from: **a**, ref. 205 under a Creative Commons license CC BY 4.0; **b**, ref. 196, Wiley; **c**, ref. 215 under a Creative Commons license CC BY 4.0.

electrophysiological and biochemical signals (Fig. 3). Their success in translation stems from their ease of use, development and testing.

Wearable technologies have been widely explored for continuous monitoring. Early wearables featured rigid electronics embedded in accessories, such as watches, shoes and headsets, for tracking physical activity and biophysical signals. Technological advancements have since diverged along multiple paths. One path has led to consumer health products, such as the Apple Watch and the Oura Ring, that have expanded access to continuous monitoring. Another path has led to clinical applications, with devices such as Biobeat and Corsano enabling medical-grade monitoring of vital signs. More recently, efforts have shifted toward skin-conformal wearables that reduce motion artefacts and improve comfort and compliance. These conformal devices have also enabled the non-invasive sampling of unconventional biofluids, including interstitial fluid, sweat, tears and saliva[124]. Such advances create new opportunities in preventative medicine, such as cytokine monitoring in sweat for detecting Crohn's disease[125] or infections[126].

Direct monitoring of electrophysiological signals

Continuous monitoring of electrophysiological signals, such as electrocardiography (ECG), electrooculography (EOG), electroencephalography (EEG), electromyography (EMG) and electrogastrography (EGG), has been achieved through mobile phone attachments, home-based portable devices and other form factors. Wearable electrophysiology monitoring could be transformative in terms of the capture and analysis of electrical signals generated by the body to provide critical insights into organ function.

In contrast to traditional 12-lead ECG, portable ECGs typically use a pair of leads on the chest and a ground electrode to detect electrical changes during heart-muscle depolarization[127,128], whereas wearable ECG sensors (such as those in the Apple Watch) provide data equivalent to only a single lead[129]. Although consumer devices from Apple and Samsung have expanded access, clinical success has been driven by medical-grade products, in particular the Biobeat patch[130] and the Zio patch by iRHYTHM (ref. 131). As with smartwatches, these patches provide single-lead ECG data, yet signal-amplification circuits and noise-reduction algorithms can mitigate the low signal-to-noise ratio of two-lead ECG designs[132]. iRHYTHM's first-mover advantage eased translational barriers, which lead to clinical adoption. By the time Apple published results from the Apple Heart Study in 2019 (ref. 133), demonstrating that the Apple Watch can detect atrial fibrillation, Zio had already validated the detection of atrial fibrillation alongside 11 other arrhythmias[134]. Portable and wearable ECGs provide an affordable solution for continuous cardiovascular monitoring[135], particularly when integrated into electronic skins[136] or smart clothing[137] to improve adherence. However, the popularity of consumer wearables, as exemplified by the Apple Watch, which received approval by the United States Food and Drug Administration (FDA) for detecting cardiac arrhythmias[138], has reduced interest in non-wearable ECG technologies.

EEG records the electrical activity of the brain through scalp electrodes by measuring voltage fluctuations from cranial neuron activity. It is used to diagnose epilepsy and sleep disorders, and supports brain–machine interfaces for cognitive and prosthetic control. EOG measures potential differences between the inner and outer canthi of the eye, enabling eye movement tracking for ophthalmological applications. Both EEG and EOG rely on direct current potentials, which are prone to drift owing to skin potentials (for EEG) or electrode polarization (for EOG). These issues can be addressed through drift-correction algorithms[139] or capacitance-based sensors that shield electrodes from environmental interference[140]. EEG and EOG electrodes are typically placed on the scalp, the nasopharynx or the ear, and have been incorporated into wearable formats such as electronic skins[141], earpieces[142] and eyeglasses[143].

EMG detects electrical signals from contracting and relaxing muscle cells, and is used to diagnose neurogenic and myogenic diseases. Continuous EMG monitoring supports applications in rehabilitation, functional analysis and sports medicine. Wearable EMG devices include armbands such as the Myo armband by Thalmic Labs[144,145], wearable patches such as the Pico EMG (ref. 146) and smart clothing such as STRIVE shorts[147].

EGG detects electrical activity in the gastrointestinal tract, particularly the stomach, for applications including motility assessment, vital-sign monitoring and the detection of slow-wave potentials[148]. A wearable patch with an electrode array for continuous and non-invasive EGG measurement[149] tested in 43 individuals differentiated EGG signals in patients with nausea and vomiting syndromes, indicating the device's potential use for monitoring gastric dysmotility.

Although the abundance of electrophysiological monitoring devices[150] complicates selection for clinical translation, there are evaluation frameworks[151] focusing on key translational challenges including convenience, accuracy, power requirements, biocompatibility and durability[150]. Devices that transfer data also face regulatory barriers related to privacy, security and storage, which are governed by the Health Insurance Portability and Accountability Act (HIPAA) and by the General Data Protection Regulation (GDPR). In the USA, HIPAA applies only if the device is provided by a covered entity, such as a healthcare provider, clearinghouse or business associate, and data are shared between the company and a covered entity[152].

Skin intolerance, which results in poor adherence, is another major translational barrier[153–155]. The device design must account for water repellency, stretchability and breathability. To improve comfort and compliance, electrophysiological sensors have been integrated into textiles[156,157]. For example, sensors were incorporated into a tailor-made long-sleeve shirt with custom sizing, which maximized comfort and usability[158]. Successful device commercialization also depends on shelf life and on the stability of key components, including membranes and coatings[159].

Direct monitoring of biochemical and electrochemical signals

Recent advances in small biosensors for the detection and quantification of biomarkers in unconventional biofluids, such as saliva, exhaled breath condensate and urine, have expanded possibilities for non-invasive health monitoring[160]. These biosensors use four main types of receptors: enzymes, antibodies, nucleic acids and molecularly imprinted polymers (MIPs). Other biochemical recognition mechanisms include ion-selective membranes and the direct oxidation of electroactive targets. A range of transducers—electrochemical optical and piezoelectric—convert binding events into measurable electrical signals, enabling accurate quantification and real-time monitoring[160].

Enzyme-based biosensors catalyse specific reactions with target biomarkers, producing detectable signal changes. Electrochemical enzymatic biosensors are the most widely adopted wearable technology. Continuous glucose monitors (CGMs) sample interstitial glucose levels using microneedles[161], and have been deployed at scale[162], with over-the-counter approval for wearable CGMs such as Stelo by Dexcom in the USA[163] and Lingo by Abbott in Europe[164]. The widespread adoption of CGMs was driven by high diabetes prevalence—133 million Americans have diabetes or prediabetes[165]—and by the rising use of glucagon-like peptide 1 therapeutics such as Ozempic, which have increased the demand for glucose monitoring[163,166].

Beyond electrochemical transducers, enzymatic sensors have been integrated into optical and piezoelectric systems in patches, microneedles, mouthguards, earpieces and contact lenses for peripheral biochemical monitoring[167]. Wearable microneedle patches can track ketone fluctuations in interstitial fluids[168]; notably, a CGM-integrated ketone sensor was introduced for ketoacidosis detection in diabetes management.

Alternative biosensor form factors include thin films on teeth for the detection of *H. pylori* in enamel[169]. Exhaled and intestinal gas sensing is another emerging approach. Electronic noses use electrochemical sensors to detect redox reactions with target gases. Proof-of-concept devices have identified musty odours on infant skin (indicative of phenylketonuria) and acetone-like odours in breath (associated with diabetes mellitus)[13], as well as markers for uraemia[14].

Continuous biosensing primarily relies on enzymatic reactions, ion-selective recognition and direct oxidation to detect key analytes such as electrolytes, glucose and lactate. However, these mechanisms are less effective at detecting trace biomarkers. For example, sweat-based biosensing is challenging because relevant biomarkers, such as hormones and proteins, are present at nanomolar concentrations or lower. Notable examples are a handheld device that used silver nanoparticles and Raman spectroscopy for the detection of creatine and cortisol in sweat with high specificity[170], and a wearable skin-conforming patch inducing sweat through iontophoresis that used graphene electrodes with MIPs to monitor multiple metabolites, including all essential amino acids[171] (Box 2). Moreover, sweat-based biomarker detection is hindered by limited understanding of how sweat concentrations relate to blood or interstitial fluid levels. Protein

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BOX 2

Wearable device for continuous monitoring of circulating metabolites and nutrients

NutriTrek is a wearable device equipped with electrochemical sensors for monitoring multiple nutrients, including all essential amino acids, through sweat. The device induces sweating through iontophoresis using carbachol-containing hydrogels, while a multi-inlet microfluidic patch samples the sweat[171]. Detection is achieved using graphene electrodes functionalized with MIPs, which act as antibody-like receptors for the selective and sensitive detection of electroactive and non-electroactive targets. Continuous sampling is enabled by applying a constant potential to the electrodes, repelling bound targets from the MIP for repeated measurements. A sodium-ion sensor and a graphene-based temperature sensor calibrate readings against skin temperature and ionic strength, which influence sensor accuracy.

NutriTrek integrates an onboard power module and a signal-processing unit that handles calibration and wireless communication, providing users with real-time, actionable nutritional insights. The system is housed in a flexible patch designed for skin compatibility, comfort and long-term usability. Alternatively, the components can be embedded in a smartwatch casing for greater convenience.

Competition in wearable devices for sweat analysis make device differentiation challenging. NutriTrek represents a substantial advance by combining biofluid sampling, selective sensing and onboard computation for the simultaneous detection of multiple targets.

concentrations, for example, can be 1,000× lower in sweat than in the blood, and sweat biomarkers may lag behind blood levels[162]. Another challenge is developing high-surface-area electrodes with specificity for target biomarkers. It is also crucial to develop sensors with ultrasensitive bioaffinity for specific disease biomarkers in biofluids other than sweat. For example, a wearable device combined affinity receptors (antibodies, aptamers and MIPs) with diverse transducers to enable trace-level biomarker detection in biofluids[172]. Another device monitored wound biomarkers alongside temperature and pH[173].

Most bioaffinity sensors are currently restricted to single-use point-of-care applications. Continuous in situ monitoring is limited by the slow dissociation kinetics of high-affinity recognition elements. To address this, synthetic receptors such as aptamers and MIPs balancing binding kinetics and sensitivity have been developed. Although sensitive transducers can be combined to enhance detection limits, the intrinsic affinity of these receptors constrains performance to micromolar-level sensitivity[174]. An emerging approach is receptor regeneration through chemical or electrochemical methods[175]. Thermal regeneration, which uses miniaturized heating elements, offers practical sensor reusability, whereas electrochemical regeneration preserves receptor integrity through pre-programmed electrical stimuli. Although semi-continuous, these sense-and-regenerate cycles can be tuned to match biomarker fluctuations.

Wearable, portable and handheld biosensors share general translational barriers, yet each type of sensor faces unique challenges. Electrochemical metal-oxide sensors require a 'burn-in' time to heat semiconductors, which affects the packaging and power design. Crosstalk between electrochemical and MIP biosensors can reduce specificity by causing unintended interactions. Moreover, devices collecting biofluids such as tears and saliva carry an infection risk, which can limit most to proof-of-concept demonstrations with uncertain translation pathways[176,177].

Direct monitoring of biophysical signals

Biophysical monitoring involves measuring and analysing physical parameters related to bodily functions and movement. Temperature monitoring is widely used to provide insights into thermal regulation and overall health. Mobile devices such as smartphones can sense skin temperature by repurposing battery temperature sensors[178], whereas wearable devices—including patches, textile-based sensors, rings and wristwatches—use resistive temperature detectors (RTDs). RTDs made from thin-film metallic materials such as gold and platinum on flexible substrates rely on the linearity between resistance and temperature[179]. Wearable thermistors, which are typically composed of semiconductor materials such as metal oxides or of conductive nanomaterial-filled polymers, exhibit nonlinear positive or negative temperature coefficients[180,181]. RTDs offer high accuracy and stability over a broad temperature range, whereas thermistors provide faster response times. Optical temperature sensors based on infrared thermography[182] and thermochromic liquid crystals also enable temperature sensing and visualization[183,184]. A limitation of these technologies is that they measure skin temperature rather than core body temperature. However, some wearables can measure heat flux to estimate core temperature[185]. Despite this constraint, continuous regional surface-temperature monitoring has shown clinical value, particularly for monitoring wound healing and diabetic foot ulcers[186].

Motion and tactile sensing is another application of biophysical monitoring. Accelerometers, gyroscopes and pressure-sensitive materials embedded in watches, clothing, shoes and flooring can detect and quantify movement, step counts and exertion. Consumer wearables already promote physical activity and help prevent conditions such as cardiovascular disease and metabolic syndrome[187]. Accelerometers in smartwatches and belts also facilitate fall detection and prediction[188,189], particularly for geriatric care[190]. In home environments, sensors embedded in floorboards[191] or carpets[192] can detect falls and monitor gait and balance[193]. And smart home systems can integrate multiple sensing modalities for unobtrusive and continuous monitoring[194].

Pressure and strain sensors are widely used for the sensing of human activity, for tactile sensing, and for vascular dynamics sensing[195,196]. Most operate through capacitive, piezoresistive or piezoelectric mechanisms. Capacitive pressure sensors detect strain-induced changes in dielectric thickness, with elastomeric materials such as polydimethylsiloxane, Ecoflex and polyurethane providing high mechanical sensitivity[197]. Piezoresistive sensors convert pressure or strain into resistance changes through conductive nanomaterial-filled elastomers (such as carbon nanotubes or silver nanowires) or conductive polymers[198,199]. Planar piezoresistive sensors have low sensitivity, which can be improved through structural modifications[200,201]. Piezoelectric sensors generate charge under stress owing to dipole reorientation. Wearable versions use flexible polymer films such as P(VDF-TrFE)[202], ultrathin inorganic films such as PZT[203] or nanowires[204]. The optimal sensing modality depends on the pressure range of the target biophysical signal: intraocular pressure monitoring (<10 kPa) requires contact lens-based technologies[205], whereas gait-monitoring pressure-sensitive shoes or carpets must function up to 2,000 kPa (ref. 206).

The monitoring of vascular dynamics, typically around 100 kPa, is implemented in limb-conformal form factors such as wristbands[207], electronic skins[208] and neck patches[203]. Key cardiovascular biomarkers—including heart rate, blood-oxygen saturation, blood pressure and respiration rate—can be continuously tracked using optical, pressure/strain or magnetoelastic generator sensors[209,210]. Wearable optical sensors use PPG to measure blood-volume changes in peripheral vessels[211], a method that is used in commercial products such

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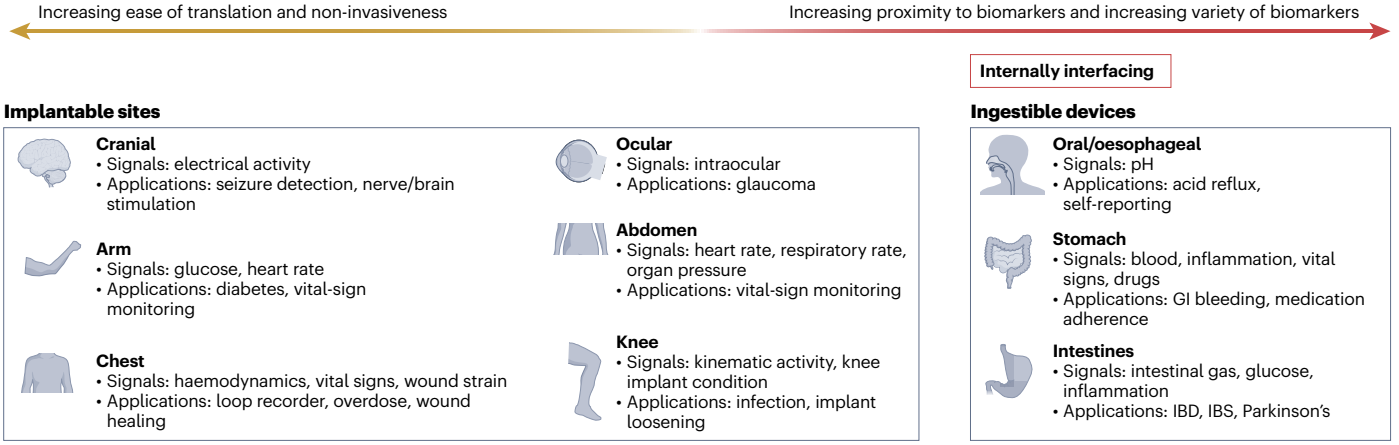

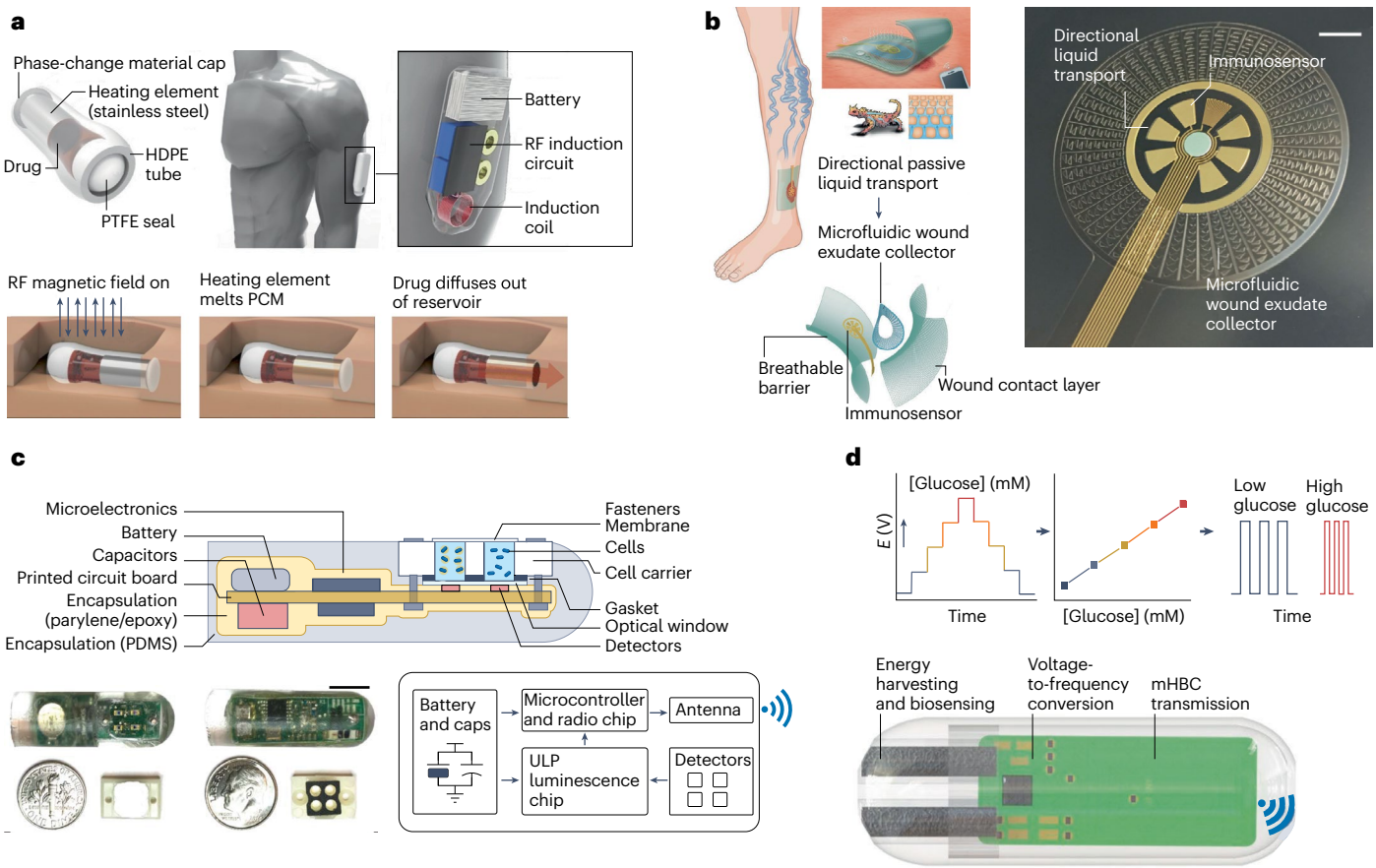

Fig. 4 | Site of action and diagnostic signals of internally interfacing technologies. Implantable and ingestible devices offer unique opportunities to directly interface with biomarkers, fluids and organs. The highlighted technologies could be capable of continuous monitoring but require further development to enable robust and long-term sensing. **a**, Implantable or wearable device for the detection and reversal of opioid overdose. PCM, phase-change material. **b**, Implantable pressure and strain sensor to monitor tendon healing. Scale bar, 5 mm. **c**, Ingestible haem-sensitive probiotic sensor for monitoring gastrointestinal bleeding. Scale bar, 1 cm. **d**, Self-powered ingestible sensor for glucose monitoring. GI, gastrointestinal; HDPE, high-density polyethylene; IBD, inflammatory bowel disease; IBS, irritable bowel syndrome; mHBC, magnetic human body communication; ULP, ultralow power. Images adapted with permission from: **a**, ref. 237, Elsevier; **b**, ref. 173 under a Creative Commons license CC BY 4.0; **c**, ref. 263, AAAS; **d**, ref. 273 under a Creative Commons license CC BY 4.0.

as the Oura Ring. Pressure sensors monitor blood pressure through subtle arterial-pressure fluctuations, whereas strain sensors on the neck or chest track respiratory rate by detecting respiration-induced movements, which is relevant to conditions such as cardiac events, pneumonia and dyspnea[212].

Ultrasound-based sensors enable deep-tissue monitoring. The sensors can capture central blood pressure[213], deep-tissue haemodynamics and cardiac performance[214,215] and organ-volume changes[216]. Recent advances have integrated adhesive hydrogel systems into wearable ultrasound devices for the continuous imaging of organs[217] and breast tissue[218]. These systems use piezoelectric transducer arrays and bioadhesive hydrogel couplants that are durable, compliant and non-dehydrating and thus allow for ambulatory use[219].

As with electrophysiological monitoring, a distinction exists between commercially successful products (such as Garmin and Fitbit) and clinically validated devices (such as Corsano and Empatica). The

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success of Corsano and Empatica in overcoming translational barriers was enabled by first-mover advantage, validation[220] and subsequent FDA approval[221] rather than from superior technology.

Several translational challenges hinder direct biophysical monitoring. Motion and gait sensors based on inertial-motion units suffer from sensor drift and noise, which requires regular calibration or sensor fusion for long-term accuracy. Pressure and strain sensors face a material trade-off: low mechanical modulus improves sensitivity but reduces durability due to inelastic stretching. Ultrasound sensors require high power for deep-tissue penetration, limiting portability. In fact, powering is a broader challenge across sensing modalities, as signal processing and filtering for the extraction of more biomarkers requires additional electrical components and increases energy demands. Moreover, because many biophysical signals can be monitored remotely, these technologies face added competition during clinical translation.

Internally interfacing technologies

Owing to their proximity to tissues and organs, internally interfacing technologies enable highly sensitive and specific monitoring of biomarkers, analytes and diagnostic signals. However, their development and clinical translation remain challenging, as implantable and ingestible devices are often invasive, pose clinical risks and are subject to strict regulatory oversight. For intermittent or continuous monitoring to be clinically beneficial, device longevity must be maximized, yet it remains constrained by the functionalities and finite lifetimes of the sensing, powering and encapsulating materials. Currently, few implantable devices, and even fewer ingestible devices, are approved for continuous patient monitoring. In this section, we highlight technologies with translational potential and discuss common challenges.

Implantable devices

Implantable devices for continuous monitoring interface with tissues, organs or organ systems to collect physiologically relevant data. Most are implanted in the arms, chest or abdomen, although other sites are possible (Fig. 4). FDA-approved neural implants record electrical signals for closed-loop seizure detection and control, vagal-nerve stimulation or deep brain stimulation[222]. Other implantable sensors include intraocular pressure monitors[223] and smart knee implants that detect infection and loosening[224].

Devices are typically inserted through minimally invasive procedures, such as catheterization[225], endoscopy, laparoscopy or subcutaneous incision or injection[226,227], yet may also be implanted during required surgical procedures[228]. Once inserted, they are secured using barbs[229], sutures or clips[230], adhesives, co-implanted structures (such as scaffolds, meshes or stents[231]) or surgically defined pockets. Devices remain in situ for their operational lifetime before either persisting as non-functional implants, dissolving partially or fully[232,233] or being removed.

Implantable continuous monitors have been explored for a range of applications. Devices can track haemodynamic parameters (such as heart rate[234], and blood volume, pressure and flow rate[225,230,235]) in patients with arrhythmias[234] or progressive heart failure[225], as well as intraocular[223] or bladder[236] pressure in patients with glaucoma or urinary incontinence. The loop recorder is widely used to monitor cardiac rhythms and palpitations[234]. Implants have also been investigated for early anomaly detection requiring intervention, such as monitoring wound healing[233] and graft oxygenation[228] or detecting post-surgical complications[224]. Another application is overdosing detection: implants have been developed to monitor vital signs associated with opioid toxidromes[237–240]. Continuous monitoring is additionally integral to closed-loop systems, such as artificial pancreases that sense interstitial glucose to regulate insulin dosing[241]. There is also growing interest in applying devices containing transplanted cells or cell clusters for continuous monitoring. In such cell therapy-based approaches, the transplanted cells, inherently responsive to target bio-factors, mediate the continuous monitoring, so that the encapsulating device instead serves to support the via bility and functionality of the cells[242,243].

Implants may use active or passive electronics, or function without electronics[244]. Active electronic implants require a co-implanted or external power source, with energy generated, delivered or stored on-site[245]. Passive or non-electronic implants lack an integrated power source and transmit data only when externally stimulated by electrical[225], ultrasonic[246] or optical[227] signals.

Beyond loop recorders[247] and continuous glucose sensors[248,249], few implantable monitors are approved for clinical use (Box 3). Advances in this area will require highly selective sensors with rapid

BOX 3

Subcutaneous implantable device for long-term glucose monitoring and diabetes management

The Eversense device by Senseonics is a subcutaneous implant for patients with type 1 diabetes and insulin-requiring type 2 diabetes. The cylindrical sensor (18.3 mm×3.5 mm) uses an optical fluorescence-based mechanism to measure blood-glucose levels. Implanted into the upper arm through a minimally invasive procedure, it provides continuous glucose monitoring for up to 180 days, eliminating the need for daily fingerstick tests.

A major challenge for internally interfacing devices is safety. Although biocompatibility is critical for all implantable technologies, achieving long-term durability without fouling is particularly difficult. The Eversense device is composed of biocompatible and stable materials (polymethyl methacrylate, 2-hydroxyethyl-methacrylate-based hydrogel, silicone, platinum and epoxy 301-2; the latter forms a hermetic seal to prevent moisture ingress). Its implantation procedure is controlled to minimize infection risk (the device is supplied sterile, and comes with dedicated insertion tools). Moreover, the sensor includes a silicone ring containing 1.75 mg of dexamethasone acetate, an anti-inflammatory agent to reduce local inflammation. Despite these precautions, there have been instances of sensor breakage, as well as side effects such as scarring and infection.

Long-term powering is another translational barrier. To enable continuous monitoring over 180 days, the implant relies on an externally worn patch for wireless power transfer. The external patch requires daily charging for 15 min; once charged, it adheres to the skin through a silicone adhesive and communicates wirelessly with both the implant and a mobile application. Without the external patch, the implant cannot collect data.

Accuracy and reliability are further challenges. To address this, Eversense requires a calibration protocol: four fingerstick calibrations after implantation, followed by twice-daily calibrations at set intervals. Missed calibrations can require restarting the process, adding to the complexity of use.

Despite the limitations, Eversense's post-calibration accuracy and biocompatibility enabled its clinical translation. Following a clinical study involving 125 participants, the device received FDA approval in 2018. This led UnitedHealthcare—a major private insurer in the USA—to begin providing coverage for the implant. As of 2023, paediatric trials have begun.

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Table 1 | Representative translationally successful technologies for continuous monitoring

Technology	Interface	Functionality	Factors that led to translational success
National Wastewater Surveillance System	Remote	Wastewater surveillance system that monitors SARS-CoV-2 RNA concentrations in the USA, to analyse disease incidences and predict future transmission.	The COVID-19 pandemic greatly accelerated the use of wastewater surveillance for public-health monitoring. The CDC converted a pre-existing system for monitoring foodborne pathogens, which facilitated rapid deployment.
Wastewater analysis by the European Monitoring Centre for Drugs and Drug Addiction	Remote	Wastewater surveillance of drugs and their metabolic product in major European cities to estimate the distribution, quantity and trends of drug use.	Successful use of wastewater analysis transformed the experimental technique into an accepted epidemiological method for public-health monitoring.
CloudMedX	Remote	Tools to aggregate and analyse medical data, such as EHRs.	The software, which integrates data from disparate databases, attracted multiple rounds of funding. Deployments and collaborations have included Mount Sinai and other hospitals.
Obesity-focused Telehealth (Form Health)	Remote	Telehealth system integrated with digital scale for weight tracking and obesity treatment. Patients can be connected virtually to their care team.	Clinical trials support self-monitoring with weight-loss success. The telehealth system was integrated with a smartphone application to enable convenient access to messages, video calls and other tools.
Eko Health	Remote	Telehealth system integrated with a digital stethoscope for virtual physical exams. Live streaming and asynchronous care are possible.	Proprietary sensors and machine-learning models were integrated with the telehealth system to enable convenient use. FDA approval for the digital stethoscope was granted in 2023 (ref. 279).
Emerald Sensor	Remote	A passive off-body sensor that uses RF waves with machine-learning algorithms to monitor respiration, heart rate, mobility, posture, sleep stages and sleep apnoea.	Tested in comparison to gold-standard methods for monitoring gait, respiration, sleep stages and sleep apnoea. Used in clinical trials for drug development.
Apple Watch	Direct	Wristwatch for the monitoring of heart rate, heart-rate variability, menstrual cycles and sleep cycles.	The watch integrates with other products in the Apple ecosystem. FDA approval for monitoring cardiac arrhythmia was granted in 2018 (ref. 280). FDA approval for atrial fibrillation history was granted in 2022 (ref. 281).
VitalPatch by VitalConnect	Direct	Wearable ECG device for the continuous monitoring of cardiac signals for 5 days.	The applications were relevant to the COVID-19 pandemic and the device was fast-tracked for translation. FDA emergency use authorization was provided in 2020 (ref. 282).
Triggerfish contact lens by SENSIMED	Direct	Silicone contact lens with a pressure sensor for measuring intraocular pressure, to monitor glaucoma progression.	Successful tests with 40 patients with a follow-up study after 2 years indicated device efficacy and safety. FDA approval was received in 2016 (ref. 283) for adults aged 22 years or older under medical supervision.
STAT-ON Holter wearable device	Direct	Wearable belt for the continuous monitoring of motor symptoms related to Parkinson's disease.	Successful patient validation studies led to a Class IIa EU classification in 2019 (https://www.statonholter.com/) and to commercialization.
BioButton by BioIntelliSense	Direct	Wearable device for the continuous monitoring of vital signs for 30 days.	The wearable device has a small form factor and a long lifetime. FDA approval was received in 2024 (ref. 284).
Discovery Patch by Epicore Biosystems	Direct	Wearable patch to sample biomarkers in sweat. The device is single use, but can be periodically replaced. Captured samples are processed in external laboratories.	The wearable patch received FDA Class I registration. The company entered into an agreement with the US Anti-Doping Agency to support screening athletes for doping.
Eversense	Internal	Implantable device in the arm for continuous glucose monitoring. The implant requires an external patch for powering, data processing and communications.	Successful human clinical trials were conducted, with <1% of individuals experiencing serious adverse effects. First FDA approval was provided in 2018 (ref. 248); coverage by UnitedHealthcare was granted in 2023.
CardioMEMS implant by Abbott	Internal	Pressure sensor implanted at the pulmonary artery. The implant monitors pulmonary-artery pressure and heart rate.	Safety and effectiveness data from human clinical trials indicated device safety and efficacy. FDA approval was granted in 2022 (ref. 285).
Multi-function spinal cord implant, Johns Hopkins University	Internal	Spinal implant with an ultrasound sensor for the continuous monitoring of post-operation autoregulation and healing.	Received considerable funding from DARPA, as well as Breakthrough Device Designation (www.hopkinsmedicine.org/neurology-neurosurgery/research/hepius/implantable-ultrasound-sensor) by the FDA.
Persona IQ by Zimmer Biomet	Internal	Knee implant with sensors to measure kinematic data to monitor patient recovery after knee-implantation surgery.	The implant was first-to-market. FDA de novo classification grant and authorization was given in 2021 (ref. 286).
Celero Systems	Internal	Ingestible capsule swallowed once a week. It remains resident in the stomach. Sensors in the capsule measure vital signs to monitor sleep apnoea.	Successful porcine proof-of-concept studies led to two successful funding rounds. Presently, the device is in development.
ID-Cap system by etectRx	Internal	An electronic capsule that monitors ingestion events to track oral-medication adherence. Transmits data to a watch-like device.	The capsule was tested in pilot clinical studies[287]. It showed accurate monitoring and limited adverse events. Patents were awarded.

and reversible binding as well as the amplification of the transduced signals[174]. Long-term operation demands materials that ensure biocompatibility, minimize fouling and prevent humidity ingress[250]. Inadequate testing or regulatory oversight has direct consequences for patient safety[234]. Wireless data transmission also raises privacy and security concerns, necessitating low-power security solutions[251]. Moreover, patient acceptability and ethical considerations present translational barriers, particularly because sham-controlled trials of implantable devices are unethical[252].

Ingestible devices

The gastrointestinal tract is rich in diagnostic markers, and ingestible sensors have been developed to detect gastric inflammation, diabetes and vital signs[253–255]. However, rapid gastric transit (2–5 h in the stomach and 2–6 h in the small intestine) limits continuous monitoring unless the devices have prolonged gastric residency[256]. Two approaches for gastric retention involve expanding hydrogels[257,258] or mechanical arms[259,260] to prevent device passage through the pylorus. One ingestible sensor used magnetic hydrogels (fabricated with NdFeB microparticles) and an external wearable magnet to maintain gastric positioning. The device, which encapsulated biosensing *Escherichia coli* Nissle 1917, fluoresced in haem solutions and enabled the continuous detection of gastrointestinal bleeding[261]. Despite hydrogel corrosion in stomach acid, biocompatibility remained intact, and mice studies showed seven-day device retention with viable probiotic bacteria. Other proof-of-concept applications include sensing inflammatory biomarkers[262,263], monitoring drug intake[264], tracking internal temperature[265] and ensuring adherence to tuberculosis therapy[266] and to psychiatric medications[267].

A major limitation of ingestible continuous monitoring is power supply. To be ingestible, devices must conform to the osmotic-controlled-release oral-delivery-system form factor (15 mm in length and 9 mm in diameter), which has an estimated retention risk of 1 in 76 million[268]. Most devices, including capsule endoscopes, follow the larger #000 capsule form factor (26 mm in length and 10 mm in diameter), which carries a 1.4% retention risk[269].

For powered devices, two strategies have been explored: wireless power transfer and energy harvesting. Wireless power has been demonstrated in capsule endoscopes[270] and in electrochemical sensors[271,272]. Energy harvesting from gastric fluid has enabled metabolite biosensing[273], although efficiency remains low, which limits clinical applicability[245]. Additional challenges include durability, biocompatibility and fibrosis[274].

As with implantable devices, the successful translation of ingestible sensors depends on multiple factors, particularly patient acceptability, power efficiency and safety[245,275]. Moving from proof-of-concept studies to clinical trials remains difficult, particularly in the USA, where FDA regulations evaluate devices on a case-by-case basis[276]. Nonetheless, the clinical adoption of ingestible devices such as the PillCam capsule endoscope has set a precedent for future translational efforts[277,278].

Outlook

Biomedical technologies for continuous monitoring offer a unique opportunity for personalized preventative healthcare. Table 1 lists examples of successful translation. However, developing technologies that are capable of true continuous monitoring, or even periodic monitoring, remains challenging. A key limitation is the scarcity of diagnostic signals that can be continuously detected, which results in a narrow range of clinically translated applications. Remotely interfacing technologies primarily monitor physiological signals, digital records and, more recently, wastewater epidemiology. Directly interfacing technologies focus on vital signs, blood glucose and sweat, whereas internally interfacing technologies monitor vital signs, blood glucose and inflammation. Expanding these capabilities to new applications requires robust and reliable device and software design.

Another common challenge is ensuring reliable and consistent monitoring over time. These technologies typically require patient adherence, which introduces design trade-offs—for example, a wearable device may prioritize comfort with breathable and skin-conforming materials at the expense of durability, whereas an implantable device may extend battery life through wireless charging but necessitate an external charging pad. This reflects a broader trade-off: longer monitoring periods require greater technological complexity, which can reduce ease of use and, consequently, adherence. Directly and internally interfacing technologies with successful clinical translation often impose operational burdens on users, such as frequent recharging, app-based interaction or secure wireless connectivity, all of which can hinder long-term adherence. Emerging research directions, such as battery-free wireless communication through ambient backscatter, offer promising strategies to enhance patient compliance.

Most of the technologies that we have here reviewed are passive and, apart from the implantable devices, non-invasive. However, beyond continuous monitoring, there is substantial potential for active and closed-loop systems that interact with the patient. For example, ingestible devices have been developed separately for drug delivery to the stomach wall and for the probiotic-based detection of gastrointestinal bleeding. Integrating such capabilities could enable a new generation of biomedical devices.

Overall, these technologies are not yet a substitute for in-person clinical care, which provides broader, more accurate and more reliable diagnostics. However, continuous monitoring technologies have value as a complement to traditional healthcare, offering caregivers critical insights into disease likelihood and progression. We envision a future in which biomedical technologies integrate seamlessly with existing health systems to support individualized preventative care.

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Author contributions
J.C. and G.T. conceptualized the manuscript and wrote the first draft. P.J.-P., P.C., M.G.S., J.T., W.G., F.H., J.K., H.-W.H. and D.K. contributed to the subsequent drafts.

Competing interests
G.T. has or currently receives equity/stock/royalties/gifts or board/advisor/consulting roles from Exact Sciences, Horizon, Pavoda, Entrega, CBSET, Avaxia, Lyndra, Novo Nordisk, SNS Nano, Hoffman la Roche, Janssen, Egalet, Synlogic, Suono Bio, Merck, Verily, Eagle Pharmaceuticals, Vivtex, Celero Systems, Bilayer Therapeutics, Teal Bio, Wired Consulting, Avadel Pharmaceuticals, Moderna, Syntis Bio, Vitakey, Absco Therapeutics, GEM-Bioscience, Bill and Melinda Gates Foundation, JHU technology transfer office, MIT technology licensing office and the MGB technology licensing office. F.H. is an employee of FormHealth. D.K. is a co-founder of Emerald. W.G. is a co-founder of Persperity Health.

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