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Review article

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Mobile medical systems for equitable healthcare

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Abstract

Major barriers to accessible healthcare include the high cost of medical devices and limited healthcare facilities. Mobile computing technologies, such as smartphones and smart watches, include high-quality hardware, such as microphones, speakers and cameras, which can be leveraged for the design of low-cost mobile medical systems intended to be remotely applied to monitor health and disease. In this Review, we discuss low-cost and accessible hardware – in particular, mobile phones – that can be used in mobile medical systems to aid in medical diagnostics and monitoring. Specifically, we outline acoustic-based systems, vision-based systems and sensor fusion systems that allow different levels of health and disease assessment, relying on the speakers, microphones and sensors of smart mobile devices. We highlight the challenges related to the deployment of mobile medical systems in the clinical continuum, including scaling, generalizability, bias, trust and privacy. Finally, we examine clinical integration and regulatory considerations with regard to mobile medical devices as well as future applications.

Sections

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Key points

- Mobile medical systems leverage smart devices and their sensing capabilities for the remote detection of health conditions.
- Acoustics-based systems rely on microphones and speakers to monitor vital signs in a contactless manner and to passively sense audible biomarkers to detect medical conditions.
- Vision-based systems combine cameras and actuators in smart devices with computer vision algorithms to track physiological signals, diagnose medical conditions and analyse biofluids.
- Sensor fusion systems combine passively measured sensor data, digital activity traces and questionnaire responses to assess digital biomarkers associated with physical, mental and behavioural health.
- The scaling and adoption of mobile medical systems require generalizability to diverse hardware designs, adaptation to real-world environments, assurance of patient privacy and mitigation of clinical bias.

Introduction

Medical resources and devices are not equitably accessible around the globe, partly owing to the high costs of medical devices and limited healthcare facilities[1–3]. For example, hearing care[4] in low-resource and rural regions often relies on outdated diagnostic hardware, donated by non-profit foundations, such as Hear the World, and patients often have to travel a long distance for hearing screenings[5]. Similarly, blood-clot tests are essential for individuals who need to take blood thinners but these tests are expensive or have to be conducted in laboratories. As a result, such patients might remain in an acceptable blood-clotting range for only 40% of the time owing to less frequent testing[6–8]. In addition, rare diseases, such as speech impediments, might affect only a small population, and thus financial incentives to invest in research and development on rare conditions might be limited.

Mobile computing technologies, including smartphones and earphones, can incorporate high-quality microphones and speakers, and cost US$40–50 second-hand, which is substantially lower than the cost of a typical medical device. Such mobile devices can be leveraged for the design of medical systems for large-scale diagnostics and monitoring through the co-design of sensor hardware and software using machine learning, wireless sensing and signal-processing tools. For example, onboard sensors, such as acoustic sensors in a smartphone, enable the detection of breathing irregularities associated with sleep apnoea[9] and opioid-induced respiratory depression[10]. Similarly, passive acoustic monitoring systems can detect lung disorders through cough sounds[11], and digital phenotyping systems[12–14] can assess physical activity or irregular speech patterns by combining data from different sensors. In addition, low-cost tools can be attached to mobile devices; for example, a paper cone to detect middle-ear fluid[15] or a 3D-printed plastic holder to collect a small blood sample for blood clot testing[16], a whistle-like device for spirometry lung-function testing[17] or a smartphone clip that guides the user to press their finger against the camera for blood-pressure testing[18].

In addition to the standard sensors included in mobile devices, such as red–green–blue (RGB) cameras, microphones, speakers and inertial measurement units (IMUs), light detection and ranging (LiDAR) sensors, depth cameras, high-frequency ultrasound, slow-motion cameras, projectors and ultrawideband radios might be exploited in the engineering of mobile medical systems. Moreover, smartphone processors including graphics processing units, such as Apple's neural engine, which are specialized cores functioning as a neural processing unit, allow on-device machine learning applications and can be explored for real-time speech translation or privacy-preserving, passive sensing of acoustic biomarkers to track neurological processes.

Smart devices, such as smart speakers, smart watches, wireless earbuds and smart eyewear, can serve as sensing platforms in mobile health sensing (Box 1). For example, active sonar and beamforming technology in smart speakers allows the measurement of the respiratory rates of infants using white noise[19] and heart rhythm assessment in adults[20]. In-ear devices can be applied for ear health assessment, for example, by measuring eardrum mobility to detect middle-ear fluid[15] and disorders[21], as well as to screen for hearing loss by measuring otoacoustic emissions[22–24]. Furthermore, wearable cameras can be applied to identify medication errors[25], and smart eyewear can be used in augmented-reality assisted surgery[26–28].

In this Review, we discuss advances, challenges and future directions in the field of mobile health systems (Fig. 1). We focus on technologies that leverage consumer smart devices (smartphones, smartwatches, smart speakers, smart glasses, smart eyewear and earbuds) as platforms for sensing and health assessments (Table 1). Thanks to the accessibility, economies of scale and sensing capabilities of these devices, they could support global access to high-quality healthcare (Box 2). We categorize mobile medical systems according to their primary sensing modality into: acoustic-based systems, which have both active and passive sensing approaches; vision-based systems, which leverage RGB cameras for motion tracking, colour analysis and scene understanding; and sensor fusion systems, which combine passive sensor data (for example, IMUs, radio signal strength and light sensors), digital activity traces and user questionnaires to measure digital biomarkers for individual-scale and population-scale health sensing, such as in digital contact-tracing systems for epidemiological tracking. Finally, we highlight mobile systems that use custom but low-cost sensing systems for healthcare monitoring.

Acoustic-based systems

Acoustic-based systems, comprising active sonar and passive sensing systems, exploit built-in speakers and microphones. Active sonar systems emit custom sound from the speaker, while recording from the microphone, thereby enabling contactless monitoring by measuring human motion, such as breathing and heartbeats, based on acoustic reflections. Such systems can also be used for point-of-care testing of ear-related health conditions. Passive sensing systems rely solely on the microphone to record acoustic biomarkers, and can be used to detect cardiac arrest events from a smart speaker[29], respiratory function over a telephone line[17] and cough sounds using a neck-worn phone[11].

Active sonar systems

Contactless monitoring systems (Fig. 2) leverage active sonar signals to track human motion by transmitting inaudible acoustic signals in the 18–22-kHz frequency band. Audible noise and interference, including human speech <18 kHz, can be filtered out, which enables privacy preservation[10]. These systems allow at-home monitoring of medical conditions. Individuals can self-administer the test and share the results virtually with their physician, thus improving access to healthcare.

In addition, individuals in home isolation or quarantine settings can be monitored, reducing the burden of regularly disinfecting contact-based wearable devices.

ApneaApp[9] is a contactless monitoring system that uses a smartphone to track fine-grained breathing and motion patterns of the chest and abdomen to detect sleep apnoea and hypopnoea events by continuously transmitting inaudible frequency-modulated continuous-wave (FMCW) signals and analysing the reflections that bounce off the chest of an individual (Fig. 2a–d). ApneaApp has been evaluated in a clinical study at a sleep laboratory against gold-standard polysomnography on apneic patients, demonstrating a high degree of accuracy in identifying sleep apnoea events. The active sonar principle in smartphones can also be applied for opioid-overdose detection[10] by identifying respiratory depression, apnoeas and large movements correlated with opioid toxicity. In a supervised injection facility and an operating room environment with simulated opioid-overdose events, this overdose detection system could accurately identify overdose events. SpiroSonic[30] exploits active sonar to measure chest-wall motion, which is transformed into indices of lung function, whereas PTEase[31] measures reflections from an individual's airway using a mouthpiece to measure the cross-sectional area of each airway segment.

Smart speakers that support an array of six to seven microphones enable fine motion tracking through complex acoustic signal-processing algorithms (Fig. 2e–g). By extracting submillimetre body displacements caused by the chest wall, smart speakers can filter out larger breathing motions and ambient noise to identify individual heartbeats and compute the heart rate and R–R intervals (interbeat interval, measured between successive R-peaks in ECG signal) for healthy users and users with cardiac abnormalities[20]. BreathJunior[19] can monitor subtle breathing motions of infants in the neonatal intensive care unit (NICU) using white-noise signals. A contactless approach is particularly desirable for infants, given that wires and contact sensors can cause rashes, burns and, in rare cases, death from strangulation[32,33].

Earable systems are designed to detect medical conditions and measure physiological signals from the ear (Fig. 3). Active sonar earable systems can detect middle-ear fluid by sending a soft acoustic chirp at 1.8–4.4 kHz through a paper funnel into the ear canal, measuring reflections to assess eardrum mobility[15] (Fig. 3a–c). An ear without fluid allows most sound to pass through the eardrum, whereas fluid buildup causes the eardrum to stiffen and reflect more sound energy. This platform shows comparable performance to specialist tools, such as tympanometry and pneumatic otoscopy, and can be performed by non-specialists. EarHealth[34] can assess ear disorders using a modified wired earphone with an in-ear-facing microphone and speaker to probe the ear. The system can detect ears that are normal, filled with fluid, blocked with earwax or that contain a ruptured eardrum. Wireless earbuds[23] and smartphone earbuds[24] allow low-cost newborn hearing screening (Fig. 3d–f) by probing the cochlea with sounds that cause cochlea hair cells to vibrate. A microphone detects the sounds produced from the vibrations to assess hearing status. This system achieves clinical accuracies comparable to the gold-standard hearing screening devices cleared by the US Food and Drug Administration (FDA), which are orders of magnitude more expensive. An open-source, portable, smartphone-based attachment[21] can be applied to measure middle-ear function and help to diagnose middle-ear disorders. The attachment probe forms a seal with the ear canal, safely varies air pressure and generates a tympanogram to quantify eardrum mobility. APG[35] uses active noise-cancelling headphones to send ultrasound signals into the ear canal to monitor cardiac events. Blood-vessel deformation leads to minute changes to the ear-canal volume, which can be tracked by this system using ultrasound reflections to measure heart rate and heart-rate variability.

Box 1 | Translational considerations

Mobile medical systems are typically based on a proof-of-concept prototype that relies on built-in sensors of a smart device and/or custom low-cost attachments[15–18] to augment the device's sensing capabilities. Translating a prototype into a deployable system requires consideration from multiple stakeholders.

Reimbursement considerations

Medical expenses can be reimbursed by insurance companies. In the USA, mobile health systems can be designed to conform to insurance codes, such as the current procedural terminology (CPT) codes used by Medicare and Medicaid. For example, smartphone-based middle-ear-fluid detection by acoustics[15] is reimbursable under the Medicare and Medicaid CPT code 92567. Mobile health companies, such as Eko Health, have been approved for a new CPT code to cover the SENSORA digital stethoscope that detects heart diseases using artificial intelligence algorithms. Integration with an insurance system might thus promote adoption.

Human factors design

Users should be considered in the design of a mobile medical system. If the intended user is a medical professional, hardware design and software user interfaces should resemble to familiar medical devices to streamline adoption and minimize usability concerns. If the intended user is a layperson, the device should present an easily interpretable medical result with actionable suggestions.

Balancing true and false positives

Mobile medical systems are often designed to produce a binary result, indicating the presence or absence of a disease or medical event. Screening or early detection tests intended for broad population testing typically prioritize achieving a high true-positive rate, even if this might result in an increased false-positive rate. This approach is justified only if the medical consequences of a false-positive result are minor, given that a positive result is typically followed up by more accurate diagnostic tests for confirmation. Diagnostic systems require a high true-positive rate and a low false-positive rate to yield an accurate result without generating unnecessary false alarm.

Passive sensing systems

Audible biomarkers in non-speech and speech sounds can be detected using ambient sensing systems that leverage voice assistants on smartphones or smart speakers to passively listen for medical events. These systems can track medical conditions long-term and thus have the potential to identify medical conditions that are difficult to detect in isolated clinic visits. However, such passive sensing systems require high levels of specificity to avoid false-positive events, must be generalizable to multiple environments with varying ambient noise profiles, and must address privacy concerns in relation to always-on microphones by operating locally without sending data to the cloud.

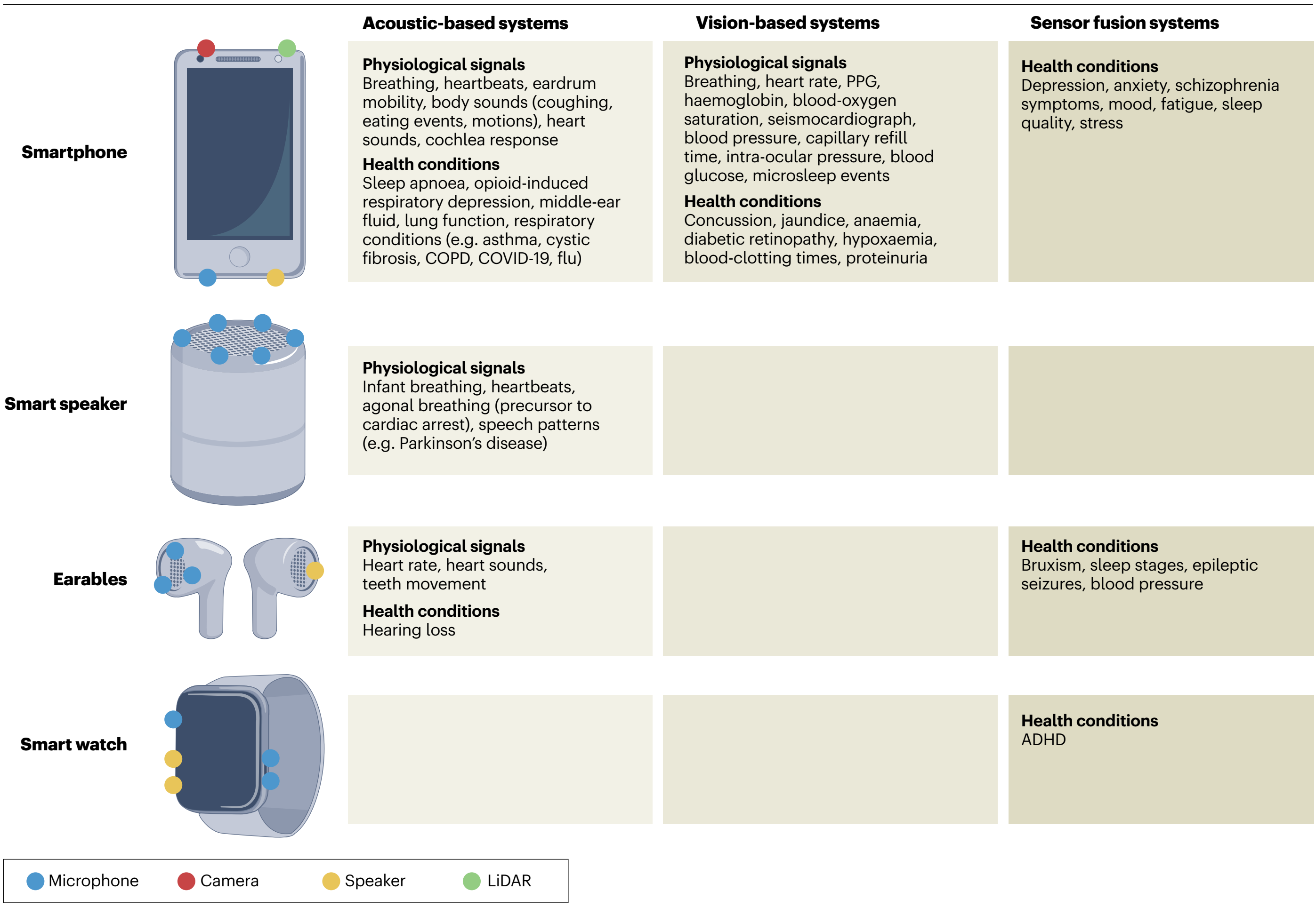

Fig. 1 | Mobile medical systems. Smart devices contain an array of sensors, including acoustic and vision sensors, which can be used for measuring physiological signals and health conditions. Passive sensor data can also be fused to obtain a readout. ADHD, attention-deficit hyperactivity disorder; COPD, chronic obstructive pulmonary disease; LiDAR, light detection and ranging.

Detecting non-speech audible biomarkers. Non-speech body sounds have been proposed as privacy-preserving biomarkers for health conditions. For example, smart speakers can detect agonal breathing[29], an audible biomarker that occurs in more than half of cardiac arrests and when an individual experiences low oxygen levels[36,37]. Such smart speakers can connect individuals that experience a cardiac arrest to emergency medical services in a timely manner. This system has been trained with 911 audio recordings of cardiac arrests to classify agonal breathing instances in real time in a bedroom setting. PDVocal[38] enables passive detection of Parkinson's disease by identifying breathing and sniffing sounds that indicate declining lung health and early signs of Parkinson's disease. BodyBeats[39] relies on a wearable piezoelectric microphone embedded in a neckpiece that is in contact with the user's skin to capture body sounds, such as eating, drinking, breathing, laughing and coughing.

Coughing, in particular, can serve as an early detection marker for a variety of respiratory conditions, such as asthma[40], cystic fibrosis[41] and chronic obstructive pulmonary disease (COPD)[42]. Privacy-preserving cough detection systems[11] analyse audio from a mobile phone placed in a user's shirt pocket or worn around the neck. To preserve patient privacy, the system applies principal component analysis to spectrograms for audio classification. For example, crowdsourced, passively sensed audio of coughing, breathing and speech can be used to detect COVID-19 (refs. 43–46) track disease progression over time[47,48] and distinguish the coughing of multiple people[49]. FluSense[50] captures coughs and speech using a microphone array, combined with thermal camera videos, to predict influenza caseloads in hospital waiting areas.

Tracking speech patterns. Speech recordings can be analysed to identify patterns associated with disease. For example, Parkinson's disease affects the vocal tract, making it challenging to speak. Therefore, the progression of Parkinson's disease can be monitored by analysing speech patterns[51,52]. StressSense[53] passively senses stress from human voices in conversations recorded in indoor and outdoor environments, and compares predictions with skin-conductance data from a wrist band. EmotionSense[54] uses acoustic features to categorize speech into broad emotional categories, such as happy, sad, scared, angry and neutral.

Physiological sensing using earables. Passive acoustic sensing systems can also be applied in earable systems that use in-ear microphone earbuds to measure physiological signals, taking advantage of the occlusion effect. This effect occurs when the ear canal is blocked, such as when wearing earbuds, causing users to perceive an amplification of low-frequency bone-conduction sounds that occur during human motion. Using an in-ear microphone, OESense[55] can sense motion to recognize step counting, activity and hand-to-face gestures, and hEART[56] measures heart rate during user motion, outperforming in-ear photoplethysmography (PPG). A custom in-ear microphone in a wired earbud design can detect low-frequency infrasonic vibrations (<20 Hz) caused by heart sounds[57]. This system can thus measure heart rate and interbeat interval, and differentiate between atrial fibrillation and sinus rhythm with an accuracy comparable to ground-truth electrocardiogram (ECG) measurements.

The raw audio stream recorded by commercial in-ear microphones is typically not accessible. Therefore, custom hardware design is required, or the microphone must be wired out to capture the audio signal. Alternatively, the in-ear speaker of earbuds can be repurposed as an input transducer to measure signals from the ear. For example, EarSense[58] uses the in-ear speaker to record teeth gestures, such as tapping and sliding, from different regions of the mouth. This system has been evaluated with interfering user motions caused by walking, nodding, cooking and cycling. Asclepius[59] converts earphones into a stethoscope, using the in-ear speaker to capture minute heartbeats from inside the ear and to reconstruct phonocardiogram signals for remote cardiac auscultation.

Point-of-care testing. Point-of-care tests can be administered on a smartphone to detect audible biomarkers. For example, SpiroSmart[60] measures lung function on a smartphone by having the user breathe in and forcefully exhale into the microphone. By analysing audio features in the time and frequency domains, the flow rate can be computed, with an accuracy comparable to that of a clinical spirometer. SpiroCall[17] extends this capability to low-end mobile phones, such as feature phones that lack the processing power to locally process acoustic data. In this system, acoustic data is sent over a standard voice telephony channel, which degrades the audio quality, to an external server that provides algorithms to estimate the flow rate. In addition, a 3D-printed whistle accessory ensures an ideal testing setup for users with lower flow rates or who have difficulty performing the test.

Vision-based systems

Cameras are prevalent in smartphones, with many featuring front- and rear-facing cameras, which can capture high-resolution images and videos. Some smartphone models further contain a LiDAR scanner with a near-infrared camera, typically used for facial identification, and slow-motion cameras with high frame rates of 960 frames per second. Moreover, extended-reality devices for virtual and augmented reality typically contain multiple RGB and depth cameras for scene understanding as well as eye-tracking cameras. Vision-based systems can also be adapted for medical testing. For example, motion-tracking systems can report on physiological signals by tracking subtle body movements in video over time using computer vision algorithms (Fig. 4a). Colour-analysis systems can detect colour changes on an individual's body related to vital signs or disease

Table 1 | Acoustic- and vision-based sensing technologies

Sensor	Sensing technique	Clinical applications	Deployed systems	Opportunities and limitations
Microphone and speaker	Active sonar	Vital signs: breathing[23,24]; heartbeats[20,35] Medical events: apnoea[9]; opioid-induced respiratory depression[10] Ear disorders: middle-ear fluid[15,21]; newborn hearing loss[22–24]	BreatheEasy, SleepScore app	**Opportunities:** continuous monitoring by always-on, low-power sensors; contactless sensing; can be integrated into most smart devices **Limitations:** sensitivity to ambient background noise; privacy concerns; dataset collection and curation; potential for false positives; requires sensor calibration across different devices
	Passive acoustic sensing	Non-speech biomarkers: agonal breathing to detect cardiac arrest[17,60]; breathing and sniffing sounds to detect Parkinson's disease[38]; coughing to detect respiratory conditions (such as asthma, cystic fibrosis, COPD, COVID-19, flu)[11,43–50]; Speech patterns: Parkinson's disease[52,222]; stress sensing[53]; emotion sensing[54] Physiological signals: heart rate; heart rate variability; interbeat interval[56,57]; phonocardiogram[59]; teeth movement[58,103]; step counting[55] Point-of-care testing: measuring lung function[17,60]	Digital Wellbeing app for Pixel phones	
	Time-of-flight ranging	Digital contact tracing	TraceTogether[109] Exposure notifications	
Camera	Motion tracking	Vital signs: breathing and heart rate[61–68], Eye testing: pupillometry[70–72]; intra-ocular pressure[73]; microsleep events[74] Biofluid sensing: blood clotting[16,77]; protein concentration in urine[76]	Google Fit for Pixel phones (breathing), Minuteful Kidney	**Opportunities:** contactless sensing; captures spatial, temporal and colour dimensions **Limitations:** privacy concerns; sensitivity to ambient lighting conditions; might require high power, thereby reducing battery life if used for continuous monitoring; requires sensor calibration across different devices; accuracy may differ across skin tones for certain tests
	Colour analysis	Blood testing: haemoglobin levels[78–80]; oxygen saturation[81,82]; blood pressure[18,83,84] Skin testing: jaundice[85,86]; anaemia[87]; capillary refill time[90] Eye testing: diabetic retinopathy; diabetic macular oedema and poor blood glucose control[89]; jaundice[87]	Google Fit for Pixel phones (heart rate)	
	Scene understanding	Medication errors[25] Medical student training[91] Surgical tool tracking[92–95]	—	

COPD, chronic obstructive pulmonary disease.

Box 2 | Low-resource considerations

Medical devices are often designed for well resourced clinical environments. By contrast, mobile medical systems can provide solutions for regions that lack clinical resources and infrastructure. However, this requires several key design considerations.

Unreliable internet connectivity
Network connectivity issues can prevent mobile devices from connecting to the internet, posing challenges for systems that rely on the sending and receiving of medical data from machine learning models to and from the cloud. Alternatively, large machine learning models can be miniaturized to allow on-device inference using techniques such as pruning[183], quantization[184] and distillation[185].

Power outages
Medical devices typically require a wall outlet for power and are not designed to work in the event of electrical failures. Electrical failures can also result in the loss of lighting, which may be necessary for mobile systems that rely on cameras and vision-based techniques. Therefore, such systems need to work under a range of lighting conditions and with only the aid of a smartphone flash.

Noisy environments
Noisy environments can pose a challenge to mobile medical systems that leverage acoustics. Noise detection and cancellation algorithms can help to mitigate the effect of noise. Furthermore, ultrasonic sensing at >18 kHz can be applied for the sensing of breathing, heartbeats and human motion[9,10,19,20].

Shortage of trained professionals
Mobile medical systems must be designed to be usable by individuals with limited expertise, and they should output actionable results that are easily interpretable.

Optimizing for limited sensing and computation capability
If smartphones with high-fidelity sensors are limited, mobile systems can be designed for low-cost feature phones, for example, to measure lung function using spirometry over a standard telephony voice channel[17] or to perform audio-based privacy-preserving cough detection[11].

(Fig. 4b). Scene-understanding systems use wearable camera systems in extended-reality devices, applying real-time computer vision algorithms to automatically streamline manual tasks, for example, in the operating room.

Motion-tracking systems

Tracking vital signs. Computer vision algorithms can track subtle changes in videos of the face captured by cameras, detecting chest movements corresponding to individual breaths and identifying head motions caused by blood flow, which can be mapped to individual heartbeats[61–68]. JoulesEye[69] uses a smartphone thermal camera system to measure respiration during high-intensity exercise and to estimate calorie burn. This system has been validated against ground-truth ECG, PPG sensors and respiration belts. Such capabilities are commercially available and can capture breathing rate by tracking chest movements from the front-facing camera.

Eye testing. PupilScreen[70] assesses the pupillary light reflex through a head-mounted smartphone display. The smartphone's flash stimulates the user's eye while recording changes to their pupil size over time to determine whether the pupil's response indicates traumatic brain injuries, such as concussions. The same test can also be performed without a head-mounted attachment[71] by combining images from a front-facing RGB camera and a near-infrared camera, typically used for facial recognition. Alternatively[72], just the RGB camera and a long-pass filter eye attachment can be applied to perform pupillometry across individuals with different levels of melanin in the irises. Intra-ocular pressure can also be measured with a smartphone-based attachment that emulates a fixed-force tonometry test[73]. CarSafe[74] measures eye events, such as microsleep events and blinking rates, which can indicate drowsy driving, using the front-facing camera. Similarly, distracted driving phone usage[75] can be detected by distinguishing drivers and passengers using their phones and computer vision techniques.

Biofluid sensing. The smartphone camera can be combined with built-in actuators for biofluid sensing, without requiring additional electronic attachments. For example, a vibration motor and camera on a smartphone can be applied to measure blood-clotting time, requiring only 10 μl of blood[16]. The blood sample is deposited into a rubber cup that contains a copper particle and that is attached to a plastic cup holder coupled to the phone. The vibration motor causes the sample to vibrate and the copper particle to move around. Computer vision algorithms track when particle motion comes to a standstill, which occurs when the blood coagulates and thickens. CapCam[76] can measure the surface tension of urine to detect elevated protein concentration levels, indicating a high risk for proteinuria; here, the smartphone is placed over a cup of urine to capture capillary waves caused by the vibration motor. The wavelength between the crests and troughs of the ripples is then used to measure liquid surface tension. The LiDAR sensor has been explored to determine fluid properties of small liquid samples[77]. When the LiDAR beam is projected onto a sample of liquid, a characteristic laser speckle pattern forms owing to light scattering from suspended particles, such as red blood cells and platelets in blood or fat and protein globules in milk. By characterizing the Brownian motion in the liquid, the viscosity states associated with coagulated and uncoagulated drops of blood can be distinguished.

Colour-analysis systems

Measuring vital signs. Colour-analysis systems can track vital signs from videos captured by a smartphone's rear-facing camera. In HemaApp[78–80], users place their finger over the back camera with the flash on and the system analyses subtle colour changes to estimate an individual's haemoglobin concentration level to screen for anaemia, with performance similar to FDA-approved haemoglobin measurement devices. The Google Pixel phone uses this technique to measure colour changes caused by blood moving through the fingertip to compute heart rate. Blood-oxygen saturation levels can be measured to detect hypoxaemia, with similar performance to pulse-oximeter readings[81,82]. Seismo[83] uses the smartphone's accelerometer to capture heart-valve vibrations and measure seismocardiography data by placing the phone on the user's chest. This is combined with PPG breathing data from the camera to compute pulse transit time and diastolic blood pressure.

However, Seismo requires initial calibration using a blood-pressure cuff for each user. By contrast, for BPClip[84], this calibration step can be bypassed with the aid of a low-cost mechanical smartphone attachment that measures blood pressure using the oscillometry principle: the user places their finger onto a spring-loaded mechanism attached to the smartphone camera and gradually applies pressure, resulting in

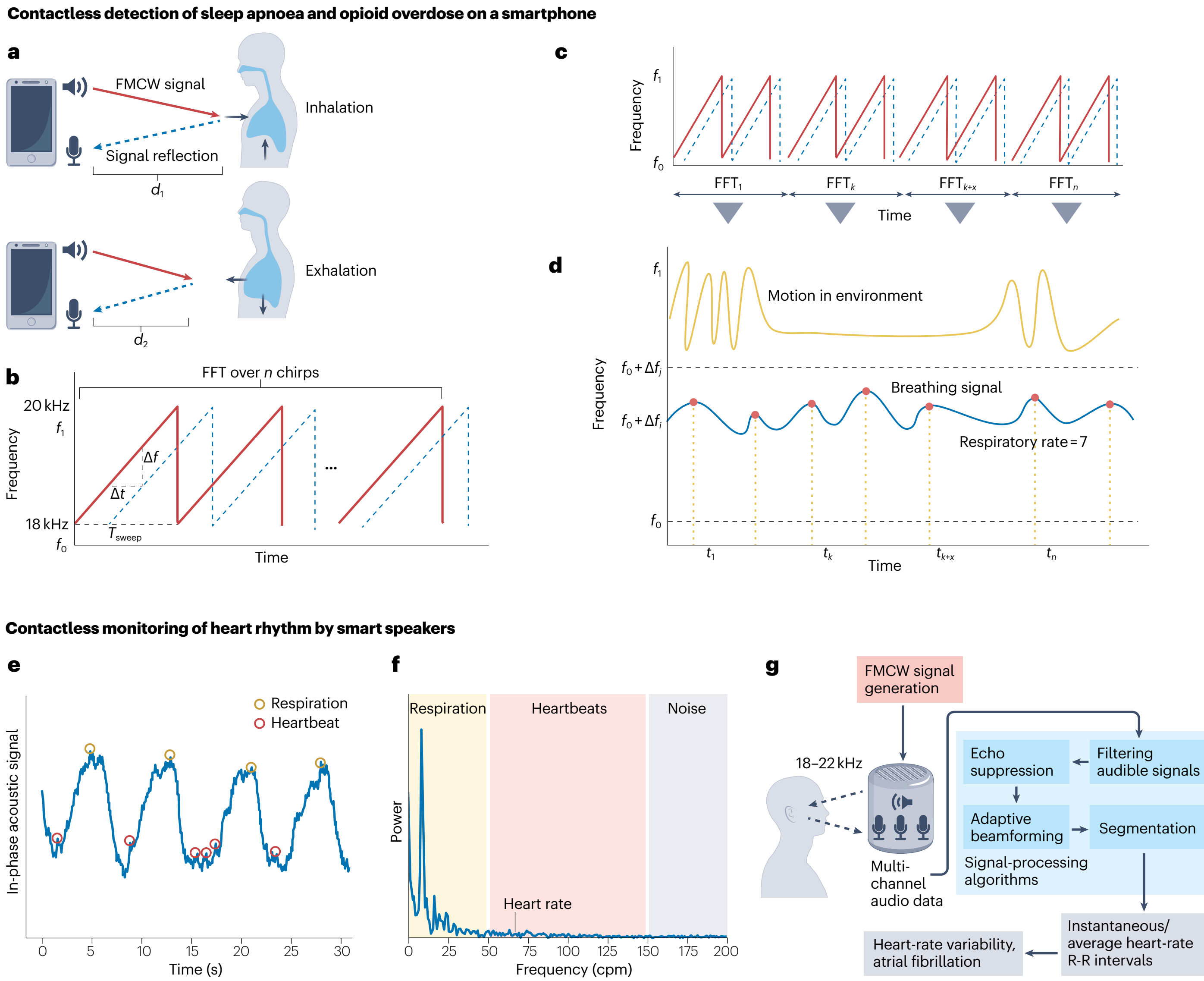

Fig. 2 | Contactless monitoring of vital signs using active sonar. **a**–**d**, Contactless detection of sleep apnoea[9] and opioid overdose[10] on smartphones. **a**, Breathing can be measured in a contactless manner using active sonar on a smartphone. The speaker transmits an inaudible, frequency-modulated continuous-wave radar (FMCW) signal, which is reflected by the chest and recorded using the microphone. Changes in the breathing signal can be related to sleep apnoea and opioid overdose. d_1 and d_2 denote the distance between the smartphone and the chest during inhalation and exhalation respectively. **b**, The transmitter continuously transmits signals, in which the frequency increases linearly with time between frequencies f_0 and f_1 over a duration T_{sweep} Reflections arriving with a time delay Δt create a frequency shift Δf. To extract the minute frequency shifts created by breathing motion, the receiver performs a fast Fourier transformation (FFT) over an integer number of chirps n. **c**, Over the course of multiple breathing cycles, reflections from the chest arrive at time delays Δt_i and Δt_e, when breathing in and out. These changes translate to distinct frequency shifts Δf_i and Δf_e, which can be estimated by taking an FFT over the chirps. FFT_k, FFT segment k; FFT_{k+x}, FFT segment k+x; FFT_n segment n. **d**, The breathing signal is located in a frequency bin corresponding to the individual's distance from the smartphone. Environmental motion occurs at a different distance and would thus appear in a different frequency bin, which can be filtered out. t_k, time point k; t_{k+x}, time point k+x; t_n, time point n. **e**–**g**, Smart speakers can be applied to monitor heart rhythms in a contactless manner[20]. **e**, When using active sonar to measure heartbeats, the breathing motion is strong, but the heartbeats are weak and difficult to observe. **f**, In the frequency domain, harmonics produced from the breathing signal spread out into the bins corresponding to heart-rate range and therefore cannot easily be filtered out. **g**, Beamforming and signal-processing algorithms running on a smart speaker system can be used to extract individual heartbeats from the signal. cpm, counts per minute; R–R interval, the time interval betweentwo successive heartbeats, measured from one R-peak to the next in the ECG signal. Panel **b**, image courtesy of S.G. Panels **c** and **d** reprinted with permission from ref. 10, AAAS. Panels **e**–**g** reprinted from ref. 20, Springer Nature Limited.

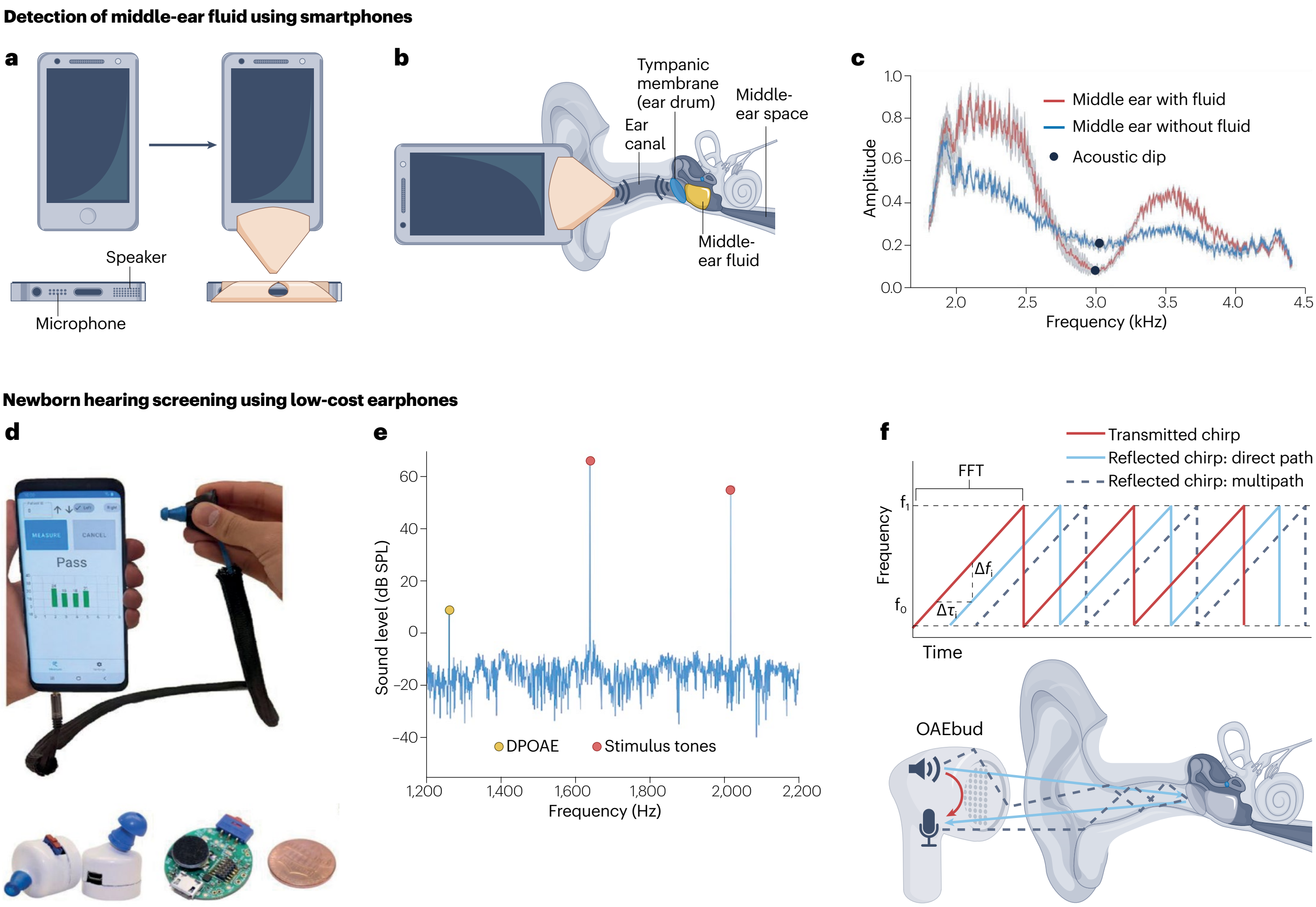

Fig. 3 | Low-cost earable systems to detect ear disorders. a–c, Middle-ear fluid can be detected using smartphones[15]. **a**, A paper funnel is attached to the phone, on which the speaker and microphone are co-located at the base. **b**, Active sonar is then applied to detect middle-ear fluid. **c**, Acoustic reflections from the ear differ depending on the presence of middle-ear fluid. **d–f**, Newborn hearing screening using low-cost earphones[22–24]. **d**, Earphones and wireless earbuds can be applied to detect newborn hearing loss. **e**, Two stimulus tones f_1 and f_2, are transmitted through each of the earbuds to stimulate the cochlea's hair cells. Using wireless sensing algorithms, the microphone detects the sounds of vibrating hair cells, which is then used as a measure of hearing status. **f**, Wireless earbuds can eliminate unwanted reflections from the ear canal and eardrum using frequency-modulated continuous-wave radar (FMCW) processing to calculate the time of arrival of reflections from the ear canal. FFT, fast Fourier transform; DPOAE, distortion product otoacoustic emissions; OAEbud, otoacoustic emissions earbud; dB SPL, sound pressure level in decibels; Δf, frequency shift; $\Delta \tau$, time delay. Panels **a–c** reprinted with permission from ref. 15, AAAS. Panels **a–f** reprinted from ref. 24, Springer Nature Limited.

brightness changes that correlate with arterial pulse amplitude and blood pressure. The oscillometry principle can also be applied without requiring mechanical attachments[18] by leveraging the smartphone's vibration motor and performing vibrometric force estimation using the onboard IMU.

Detecting disease. Colour-analysis systems can detect diseases from images captured by smartphone cameras. For example, BiliCam[85,86] is a low-cost system that identifies jaundice in newborns by detecting yellow discolouration of their skin. Here, a colour-calibration card is used to standardize across different smartphones and lighting conditions, enabling bilirubin estimation, which is as accurate as when determined by blood tests and comparable to readings from non-invasive bilirubinometers. BiliScreen[87] can identify subtle discolourations in eye images to detect mild, visually imperceptible forms of jaundice. The test is performed using either paper glasses with calibration markers to colour-balance across different lighting conditions or within the controlled lighting environment of a head-mounted display. Calibration-card-free visual detection of anaemia can be achieved using image metadata to normalize across lighting conditions[88]. Smartphone images also allow the detection of eye conditions that typically require a specialized camera to capture retinal fundus photos. Using a deep learning model, these images can detect eye conditions, such as diabetic retinopathy and diabetic macular oedema, as well as poor blood-glucose control[89]. CapApp[90] measures capillary refill time, which is the time taken by blanched skin to return to its resting state after pressure has been applied. Here, a user presses their finger onto the camera of a vibrating phone and the amount of applied pressure is measured through dampened vibrations at the IMU, in addition to measurement of the brightness amplitude at the finger.

Scene-understanding systems

Cameras on extended reality devices, such as the HoloLens, heads-up displays and augmented-reality glasses have been explored for use in the operating room[26–28]. For example, wearable camera systems can detect clinical medication errors by classifying drug labels on syringes and vials and flagging if labels might be mismatched, indicating an error[25]. HoloLens can serve as an augmented reality-based system for surgical education to guide catheter placement into the brain ventricular system, a common neurosurgical procedure[91]. Video data captured from the egocentric point of view can also be applied for surgical tool detection and tracking to assess surgical skill[92–95]. However, vision-based extended-reality systems rely on sampling from multiple high-resolution cameras, which requires high power and computational complexity to run machine learning models on streaming video data. Accurate and low-power scene-understanding systems would thus need to be optimized, including duty-cycling cameras, custom neural architecture designs and mechanisms to offload data to edge servers, while operating in real time.

Sensor fusion systems

Sensor fusion systems combine data from smartphones and wearable devices, such as smart watches and smart bands, to build a digital phenotype of a user and infer their behavioural and physiological health states (Table 2). Such systems can also measure digital biomarkers that correlate with measures of mental health[13,96–98]. Therefore, smart fusion systems allow for passive monitoring of the onset or progression of medical conditions over time. These systems typically leverage three main sources of data: passive sensor data, including IMU readings (accelerometer, gyroscope, magnetometer), global positioning system (GPS) location, network identifications and signal strengths (Wi-Fi and Bluetooth), ambient light, barometric pressure and skin temperature; digital activity traces, including call logs, internet browsing history, app usage and communication patterns (texts and emails); and questionnaires that periodically assess physiological, behavioural and mental state through tools such as ecological momentary assessment (EMA) and patient health questionnaires (PHQ). These sources of data can be applied to sense physical, behavioural and mental health conditions. To assess physical health, measurements can be combined across different built-in sensors, such as the IMU, or low-cost add-on sensors, such as electroencephalography (EEG) sensors, to obtain objective measures, such as blood pressure. Integrating multiple modalities can enable more accurate assessments. Behavioural health can be evaluated through inferences of raw sensor data to deduce digital phenotypes, such as activity and sleep patterns as well as indoor and outdoor mobility patterns, which are then correlated with measures of behavioural wellbeing, such as mood and loneliness, which can be obtained through questionnaires. Mental health monitoring relies on correlations between passive sensor data and digital activity traces to assess symptoms of conditions such as depression[96,97] and schizophrenia[13,99,100].

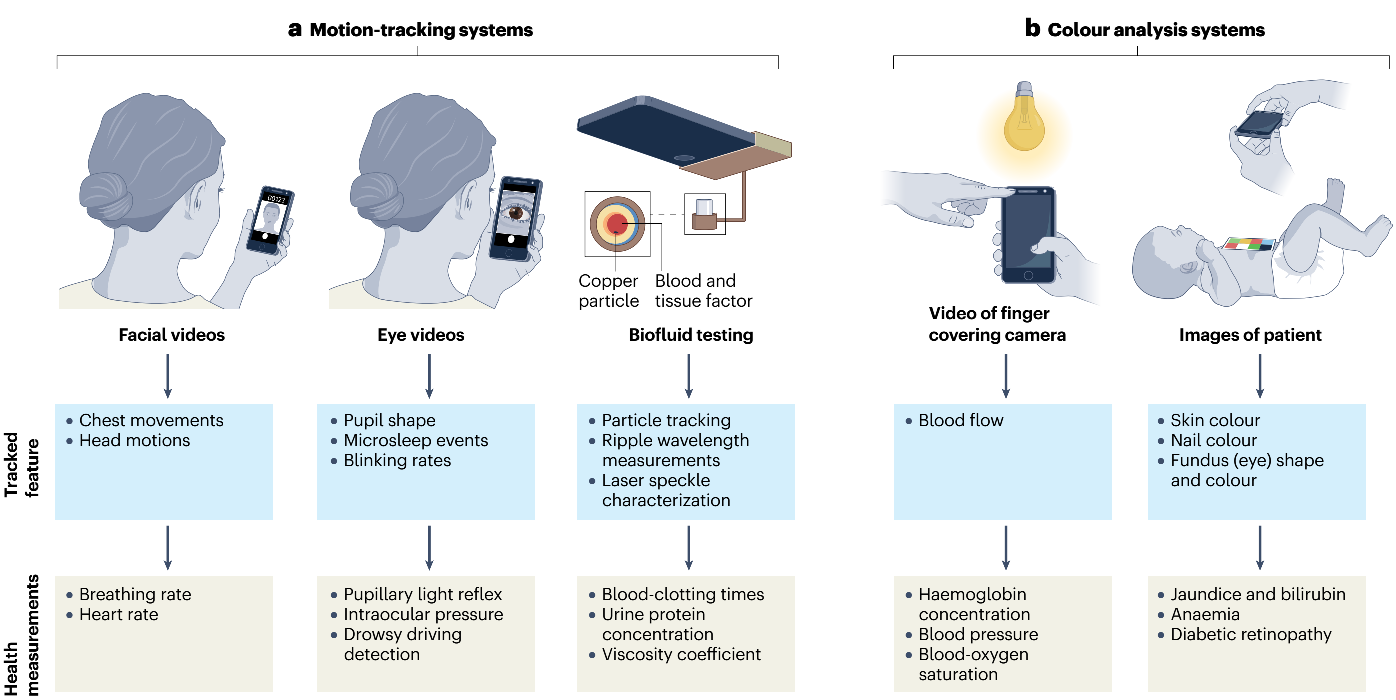

Fig. 4 | Vision-based systems. a,b, Vision-based systems leverage images and videos captured from the smartphone's front- or rear-facing camera. Computer vision algorithms based on motion tracking[16,76,77] (**a**) or colour analysis[78,85] (**b**) can be applied to measure physiological signals and health. Using motion-tracking algorithms, biofluid testing can be performed, for example, by tracking the micro-mechanical motions of a copper particle in a vibrating sample of blood inside a plastic cup holder attached to a smartphone to measure clotting times[16]. Panel **a**, image courtesy of ACM, and adapted from ref. 71, CC BY 4.0 (https://creativecommons.org/licenses/by/4.0/), and reprinted from ref. 16, Springer Nature Limited. Panel **b**, image courtesy of Shwetak Patel.

Table 2 | Sensor fusion systems for behavioural health monitoring and digital phenotyping

Sensor	Digital phenotype	Digital traces	Medical findings
IMU	User activity (such as exercise level)	Call logs Text messages, email patterns	Depression[12,14,96–98,123] Anxiety[98]
Microphone	Social interaction levels		ADHD[125] Schizophrenia symptoms[13,99,100]
GPS	Outdoor mobility patterns	Internet browsing history	Mood[117]
Wi-Fi and Bluetooth	Indoor mobility patterns	App usage	Fatigue[14] Sleep quality[14,107]
Ambient light	Sleeping patterns		Stress[123,127]
Camera	Event logging		
Barometer	Elevation		
Heat sensor	Body temperature		

ADHD, attention-deficit hyperactivity disorder; GPS, global positioning system; IMU, inertial measurement unit.

Physical health

Individual-scale sensing. The health outcomes of individuals with multiple sclerosis, including depression, fatigue, sleep quality and global symptom burden, in the stay-at-home period during the COVID-19 pandemic, could be predicted using smartphone sensor data (call logs, GPS location, screen activity), physiological data from a Fitbit activity tracker (step count, heart rate, sleep and wake times) and health questionnaire data[14].

Earable systems can also exploit sensor fusion by using the onboard IMU and custom sensors to measure signals from the ear. For example, the IMU on the eSense[101,102] earbud platform can measure and classify teeth grinding and clenching behaviour to detect bruxism[103]. eBP[104] measures diastolic and systolic blood pressure from the ear canal using an in-ear air pump, pressure sensor and valve; here, pressure is applied to the outer ear canal by a microcontroller and an in-ear light-pulse sensor measures the PPG signal. WAKE[105] detects microsleep events using a custom earpiece to capture brain waves by EEG, eye movements by electrooculography (EOG), facial muscle contraction by electromyography (EMG), and skin conductivity by electrodermal activity. LIBS[106] measures brain activity, eye movement and muscle contraction using EEG, EOG and EMG signals, respectively, from an in-ear device. These signals are recorded as a single mixture and a signal-separation model is then applied to isolate individual signals and classify different sleep stages. EarSD[107] is an ear-worn system that enables the detection of epileptic seizures by sensing and classifying signals from EEG, EMG and EOG sensors.

Population-level sensing. The sensors of smart devices allow population-level sensing for public health and epidemiological surveillance. For example, digital-contact tracing[108–110] can be used to track a user's exposure to individuals potentially infected with SARS-CoV-2 using smartphone sensor readings. Exposure is typically defined as being within a 1 m or 2 m range of an infected person[111]. Although GPS location traces from a smartphone can provide coarse-grained location estimates with a distance resolution of 3–5 m, they do not provide sufficient accuracy to assess whether two people are within social distance. Furthermore, GPS cannot distinguish whether there is a wall or ceiling between two users and is thus unreliable indoors. Bluetooth-based solutions, such as TraceTogether[109] and exposure notifications, rely on the received signal strength to infer proximity; however, such distance estimates might be unreliable. NOVID uses inaudible acoustic signals and time-of-flight ranging to measure the distance between smartphones. Smartphone clocks are able to measure the time down to milliseconds, and so the system can record when two phones have sent and received messages. By multiplying the difference between these timestamps with the speed of sound, NOVID produces a sub-metre distance estimate. However, in acoustic-based systems, signals can be attenuated by obstacles, and reflections can thus occur in a multipath-rich environment, which can interfere with the direct line-of-sight signal.

Global-scale datasets of passively measured accelerometer data have been analysed to reveal inequalities in the distribution of physical activity across different geographical regions, which might serve as a predictor of obesity prevalence. In addition, the walkability of a city might be associated with greater activity levels[112].

Behavioural health

Sensor fusion systems[113] might also predict behavioural health based on passively sensed data. For example, SoundSense[114] uses raw audio data from the microphone to coarsely classify sound into speech, music and ambient sound, which can then be more accurately divided into specific sound classes. These classified acoustic events can inform an audio diary of daily events, recorded over time. Moreover, sleep duration can be assessed according to smartphone usage patterns, recharge events, ambient light sensor data and accelerometer data[115]. However, continuous data sampling from multiple power-demanding sensors (particularly if the device is not charging) can substantially drain battery life. To address this challenge, JigSaw[116] contains power-efficient pipelines to adaptively adjust sensor sampling rates; here, algorithms are applied to measure user activity speed from accelerometer data and accordingly to adjust the GPS sampling rate. An activity classifier is then applied to the raw accelerometer data to enable users to track their daily calorie expenditure and carbon footprint. The mood-sensing system MoodScope[117] takes an alternative approach by relying solely on digital traces of smartphone usage patterns (app usage, website browsing behaviour, email, text message and phone call patterns as well as location data) to make inferences about a user's behaviour.

Sensor fusion systems can also promote positive changes to user behaviour. For example, BeWell[118,119] applies quantitative scores to indicate whether a user is averaging adequate levels of sleep, aerobic activity and social interaction per day. These scores are presented to the user on their smartphone lock screen to promote wellbeing. MyBehavior[120] combines passively sensed data with manual logging of food intake and exercise patterns to provide personalized suggestions for calorie loss. UbiFit[121] leverages accelerometer and barometer data to classify a user's physical activities, which are presented on the display to encourage exercise. The SmartGPA[122] system measures a user's studying and socializing patterns to predict academic grade point average (GPA) performance, which could enable timely interventions for improving academic performance.

Mental health

The long-term mental health trends of populations might be assessed by smart sensor systems. For example, the digital phenotyping system StudentLife[12] has been applied to conduct a behavioural health study in a class of college students over the period of a school term. The system captured activity information (stationary, walking, running, driving, cycling) from IMU data, outdoor mobility patterns from GPS samples, indoor mobility patterns from Wi-Fi scan logs, conversation levels from the microphone audio stream, sleep duration from ambient light readings and phone usage logs. Here, sensor data correlated with measures of mental wellbeing (depression, stress, flourishing, loneliness), which was assessed through user questionnaires. Several systems have focused on further understanding the dynamics and effects of depression in the college population[96,97].

Features could be developed on the basis of passively sensed data that relate to depression symptoms, as defined in the *Diagnostic and Statistical Manual of Mental Disorders*, 5th edition (DSM-5)[96]. These features correlate with self-reported Personal Health Questionnaire depression scale PHQ-8 and PHQ-4 scores. Data from smartphones and fitness trackers can further be used to identify depression symptoms without requiring periodic recalibration, using ground-truth questionnaires[97]. Here, depression scores are measured once at the beginning and once at the end of the semester, revealing post-semester depression 11–15 weeks before the end of the semester, thus allowing pre-emptive intervention. In a smartphone and ecological momentary assessment study, biomarkers of depression ($P = 0.03$) and anxiety ($P < 0.001$) in college students were found to statistically significantly correlate with fluctuations in COVID-19-related news during the COVID-19 pandemic[98]. Similar patterns have been identified in other populations[14].

Digital phenotyping systems can also be applied in clinical studies to remotely assess new quantitative biomarkers in individuals with medical and psychiatric conditions[123,124]. For example, LemurDx[125,126] uses smartwatch accelerometer data to measure increased hyperactivity from hand motion, which could indicate an attention-deficit hyperactivity disorder (ADHD). Trained with coarse activity information about children, provided by parents at the end of the day, the system can classify different activity patterns (sleeping, sitting, household activity, exercise, not wearing a watch). These motion data can then be combined with location data from GPS, a heart rate sensor on the smartwatch and Bluetooth scans.

CrossCheck[13,99] and an approach using encoder–decoder neural networks[100] can predict the severity of psychiatric symptoms in individuals diagnosed with schizophrenia (seeing things, hearing voices, worrying about being harmed) to aid in disease monitoring and preventing relapse. Digital phenotyping systems[127] have also been evaluated in a population of resident physicians, which are at risk of workplace stress and developing mental health symptoms, identifying physiological indicators of stress-resilience from physical activity, sleeping behaviour, heart rate and mood.

Custom low-cost sensing systems

In addition to mobile systems that make use of onboard sensors and smart devices, custom low-cost sensing systems enable alternative forms of healthcare monitoring. Furthermore, mobile medical systems allow large-scale digital epidemiology in the form of contact tracing.

Wearable sensing systems

Joey[128] is based on a conductive fabric necklace that can measure the heart and respiration rate of infants through ECG signals during kangaroo mother care (chest-to-chest skin contact between the infant and a caregiver). Here, diffusion-based denoising models disentangle the ECG signals from the caregiver and the infant. PPG sensors, usually used in pulse oximeters and wearable devices to estimate heart rate, blood-oxygen saturation and other physiological parameters, provide less accuracy in individuals with dark skin because their higher melanin levels affect the absorption of laser light. MagWear[129] tackles this issue by leveraging biomagnetism to measure heart rate and respiratory rate through a small magnet at the wrist. The magnet pushes blood flow, and biomagnetic field signals are then induced thanks to the ions produced by each heartbeat. This can be measured with a giant-magnetoresistance sensor. Painometry[130] relies on a hat-shaped form factor sensing platform that measures EEG, PPG and galvanic skin response to objectively quantify a user's pain perception. Custom smart rings[131–133] with integrated IMU and PPG sensors might also be applied to monitor heart and respiration rate.

Instrumenting health devices

Health devices can be equipped with additional sensors to enrich health monitoring. For example, ToMoBrush[134] can be applied to electric toothbrushes, using microphones to extract the acoustic resonance of an individual tooth and assess its dental condition. IOTeeth[135] integrates piezoelectric sensors in a dental retainer platform to monitor dental occlusal diseases, which can result in tooth loss, by tracking teeth biting and grinding activities. MechanoBeat[136] can be applied to create 3D-printed tags that oscillate at a distinct frequency, which can be sensed with an ultra-wideband radar array to detect when a user interacts with a medicine pill bottle. Similarly, an insulin pen can track the number of times insulin is dispensed[137].

Real-world challenges

Mobile health systems should work in different environments and for smart devices from different manufacturers. They should also be designed to mitigate biases and ensure trust, which requires policies enforced by regulatory bodies. Moreover, mobile health systems need to be integrated with clinical care processes.

Scaling to real-world environments

Deploying mobile medical systems in real-world environments faces challenges that are typically not seen in the controlled environments they were initially prototyped in.

Uncontrolled environments. Real-world testing environments can be complex, with suboptimal testing conditions, such as different levels of background noise and ambient lighting conditions, as well as human motion. Therefore, systems need to be designed to detect and tolerate real-world conditions. For example, smartphone-based systems that can detect opioid-induced depressed breathing require filters to remove audible environmental noise and distinguish breathing from other body motions[10].

Dataset collection. Scaling to multiple environments might require the collection of large amounts of diverse data, which can be costly and difficult. Efficient dataset collection approaches, such as crowdsourcing, and data-augmentation methods to create synthetic datasets, enable scaling across a large number of environments. For example, to collect breathing sounds from different smartphones and environments, the Amazon Mechanical Turk crowdsourcing platform has been harnessed to recruit individuals, who recorded their sleep with their smartphone microphone[29]. These recordings were subsequently used to train generative artificial intelligence (AI) models, such as generative adversarial networks, to produce synthetic data.

Data heterogeneity and incompleteness. Sensor fusion systems, such as those used for digital phenotyping, measure data from multiple sensor modalities (for example, IMU, microphone, light sensor, network signal strength), digital activity traces (for example, app usage levels, texting behaviour) and data types (for example, time series, survey results, symptoms). Machine learning models are typically designed to work with a single data type and cannot easily integrate heterogeneous data streams[138]. Multimodal machine learning models aim to jointly learn from different data types, which requires addressing challenges in data representation, translation, alignment, fusion and co-learning[139]. Furthermore, they cannot easily deal with data that are missing, incomplete or noisy, which can be produced by sporadic and uncontrolled usage patterns[138]. Therefore, data cleaning and preprocessing, in the form of noise and outlier removal, as well as data interpolation[138], are typically required before machine learning models can be used.

Generalizing to diverse hardware designs

Medical devices are typically purpose-built for a standardized hardware design, which often differs from that used in smart devices and sensors. Furthermore, sensors, such as microphones and speakers, can degrade in quality over time. To address this, new clinical data can be collected for each new device; however, this approach can be time-consuming or infeasible, given the diversity of newly launched devices.

Sensor-calibration techniques, such as colour-coded reference cards[85–87] and image metadata[88], can be applied to normalize colour profiles for images captured across different smartphone cameras. A standardized acoustic cavity can be used to calibrate the acoustic frequency response of a speaker and microphone[24], which allows scaling of new devices without the need to collect additional clinical data. Systems that leverage the IMU for tasks, such as step counting, rely on features such as normalized auto-correlation, which work across different accelerometer sensitivities and sampling rates[140,141].

However, not all hardware sensors can be calibrated by the user upon use. For example, in the case of contact-tracing apps that rely on Bluetooth signal strength to determine whether two smartphones are close to each other, each smartphone model might have a different Bluetooth radio chip, antenna layout and phone operating system version, which could report different readings for the same distance. Obtaining the per-phone mapping from the received signal strength indicator to distance typically requires manual readings collected in an anechoic chamber, which is a time-consuming procedure. TraceTogether, a Bluetooth-based contact tracing system, can perform this manual calibration process.

Mitigating bias from sensor-based systems

Medical mobile systems that do not address clinical bias can perpetuate health inequities. For example, systemic biases can be propagated in systems that are trained with chest X-ray images[142], diabetic retinopathy fundus images[143], clinical interviews and records[144] and other medical records[145]. Therefore, the FDA has released an action plan with the aim of supporting improvements to models after deployment. Bias might be mitigated through the generation of synthetic data by generative AI systems[146], such as generative adversarial networks[147], variational autoencoders[148] and large language models, particularly for under-represented disease classes or severe disease states[149–151]. Synthetic data can also be generated using physics-based simulations in silico or benchtop models in vitro[152–154].

Gender bias. Women and men show differences in ECG parameters during adolescence, with women typically having a faster heart rate compared to men and differences in QT interval (ventricular depolarization and repolarization time), QTc interval (heart rate–corrected QT) as well as QRS complex (ventricular depolarization amplitude and duration) owing to hormonal differences. These differences can result in greater levels of risk for certain diseases, with women aged 20–40 having a threefold greater risk of arrhythmic-related cardiac events compared with men[155]. Mobile ECG systems can show reduced accuracy in women if they are trained primarily on data from men, which might lead to increased false positives for women in the ECG-based diagnosis of ischaemia[156]. This gap might be partly addressed by increasing awareness during medical training and by adapting models to physiological differences.

Women and men also differ in their gait — for example, in kinematic and kinetic variables in both healthy individuals and those with osteoarthritis[157,158], which can be applied for automatic gait-based sex classification[159]. These differences should be accounted for in mobile medical systems, particularly in those performing activity recognition, through a balanced dataset or by incorporating sex-specific gait features into machine learning models to reduce bias.

Age bias. Mobile medical systems that measure physiological signals such as PPG and blood pressure should consider age-related physiological differences. The PPG waveform at the ear, finger and toes changes with age owing to differences in physiology[160]. In particular, increased arterial stiffness might affect key signal features in the PPG waveform of older individuals, making them more challenging to detect[161]. Pulse oximetry measurements leveraging PPG can be biased owing to motion artefacts, for example, in children. Therefore, large probes should be adapted to the small fingers of neonates and infants, and devices should be calibrated with data from healthy young adults[162]. Moreover, age-matched ranges should be used in the evaluation of individuals with vascular disease[160]. Blood-pressure measurements are considerably affected by age, with systolic blood pressure being increasingly underestimated and diastolic blood pressure being increasingly overestimated with increasing age, compared to invasive aortic blood-pressure measurements[163]. Therefore, personalized blood-pressure measures are required to normalize for age.

Skin-tone bias. Wearable sensing systems measuring arterial oxyhaemoglobin saturation by pulse oximetry perform worse in individuals with darker skin tones compared to those with lighter skin tones, owing to differences in skin absorption and scattering characteristics influenced by melanin levels[164,165]. The calibration parameters of these devices are often biased towards individuals with lighter skin tones[166], and inaccuracies in pulse oximetry measurements can result in the under-detection of hypoxia and sleep apnoea[167,168]. Importantly, such measurements are used by insurance companies to determine eligibility for medical reimbursement, and thus, systemic errors in pulse oximetry measurements can further promote inequities in healthcare.

The low performance of PPG on darker skin can be addressed by the MagWear system[129]. Similarly, inaccurate pupillometry results in individuals with darker irises can be addressed through the use of a smartphone-based filter to perform the test in the far-red visible light spectrum[72].

Cultural bias. Mobile systems that rely on speech detection and transcription to assess mental health may perform poorly on a diverse range of accents if primarily trained on a single accent[169,170]. Speech-based health-sensing systems that rely on vocal prosody to detect mood may function differently for English compared to tonal languages, such as Mandarin[169,170]. Digital phenotyping systems may leverage psychological models of stress, anxiety and depression, which cannot be generalized across cultures[171]. Diet-tracking systems for individuals with diabetes are often optimized for specific diets and may thus inaccurately estimate the glycaemic response to diverse foods[172]. Moreover, religious headwear should be accounted for in systems that require head-mounted sensors, such as EEG sensors or heads-up displays[173].

Medical history bias. Pre-existing medical conditions can act as a confounding factor, affecting the accuracy of sensing technologies. For example, arrhythmias and irregular heart rhythms affect the shape of the PPG waveform and can affect measurements of heart rate, heart rate variability and blood-oxygen saturation[174]. Diseases that affect movement, such as Parkinson's disease, can result in motion artefacts in PPG waveform measurements. Medications can also introduce biases; for example, beta-adrenergic-blocking drugs can increase heart-rate variability[175]; endocrine medications for thyroid disease can affect drug metabolism[176]; and psychiatric medications, such as selective serotonin reuptake inhibitors and antidepressants, affect the heart rate[177] and can cause sleep disorders, such as apnoea and bruxism[178]. Such medication-induced variations can lead to false-positive or false-negative readouts in medical devices that monitor sleep or cardiac conditions. Therefore, patient-specific calibration protocols and alternative sensing modalities might be required.

Digital literacy bias. Lack of or limited literacy of users and/or healthcare professionals as well as limited implementation of electronic health record systems can negatively affect the effectiveness of mobile medical systems[179–181]. This might be addressed by providing user interfaces and instructions that rely on graphics, video and voice guidance. By integrating mobile medical systems into the continuum of care, provider-assisted onboarding and training can also help to increase adoption of these systems. In addition, public health policies to increase access to computing devices and training on digital health technologies might promote the deployment of digital health systems.

Trust in mobile health systems

Establishing trust is an important factor in the deployment of mobile health systems. Sensors in mobile health systems can capture sensitive data beyond health information. For example, cameras and microphones might capture sensitive and identifiable data, such as the user's face, surrounding environment, data from bystanders[61–68] and voice data[38]. Although privacy concerns might be partly addressed by technological mitigation strategies, such as data processing at the edge, data obfuscation, filtering and anonymization, data leaks, unauthorized access and data exploitation remain concerns[182].

Maintaining patient privacy

Built-in privacy-preserving technologies can minimize data leakage while maintaining device performance.

Edge computing. Mobile medical systems that rely on machine learning models to process sensor data might send data to the cloud for further processing, which bears the risk of data being compromized in transit or at the server. Running algorithms and models on an edge computing device, such as smart devices, mobile central processing units and mobile graphics processing units, can help to preserve patient privacy. However, the model has to be optimized for the constrained computational resources of mobile or embedded devices, while maintaining a high level of clinical accuracy. Optimization techniques, such as pruning[183], quantization[184], knowledge distillation[185], model compression[186], low-rank factorization[187] and neural architecture search[188], can help to reduce model size, inference time and memory footprint to enable deployment on edge devices.

Federated learning. By re-training a model with new patient data using federated learning[189,190], local models can be trained on edge devices, and only encrypted model updates are sent to a central server, where they are aggregated. An updated model is then sent back to the local devices. This strategy allows hospitals to comply with privacy regulations, such as the Health Insurance Portability And Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR), by ensuring that patient data stays within the institution[191].

Privacy-preserving techniques can also be designed at the hardware level; for example, inaudible frequencies can be used in sensors that assess behavioural biomarkers in digital phenotyping systems[192], or depth or thermal cameras can be applied instead of RGB cameras for vision-based systems[50] At the software level, secure enclaves and homomorphic encryption can be used[193].

Improving explainability

Black box machine learning models, for which the underlying mechanistic information is lacking, might also compromise trust. For patients, intuitive and non-technical (plain language) explanations and colour-coded risk scores can increase the accessibility of medical information[194]. In addition, generative AI can create synthetic medical images for patient education[195]. Healthcare personnel can benefit from saliency maps[196] that highlight relevant regions in a medical image to help them to understand a model's focus and build trust in the system. Similarly, concept-based explanations can translate a model's prediction into familiar medical concepts[197]. Concept activation vectors[197] can be used in the diagnosis of diabetic retinopathy from retinal fundus images[198], providing a score for different diagnostic concepts, which might help in the interpretation of a model's predictions and flag instances in which healthcare professionals disagree with the model.

Shapley values[199] quantify how much each feature contributes to a model's prediction. For example Prescience[200] uses Shapley values to provide a numeric representation of hypoxaemia risk (odds ratio) and quantify the contribution of pulse level, tidal volume, body-mass index and other factors to the prediction. Local interpretable model-agnostic explanations[201] allow physicians to assess how perturbations to these different features affect the model's predictions and whether the model's responses align with their medical knowledge.

Building trust with patients and the public

The integration of mobile medical systems into clinical workflows and endorsement by healthcare professionals and institutions can increase a patient's trust. Ensuring compatibility with electronic health record systems and telemedicine platforms can further facilitate adoption and reinforce the credibility and reliability of systems. Patient–provider interactions are also important in building trust through face-to-face interactions, training and guidelines for standardized use[182]. Moreover, deployment by reputable service providers, publications and endorsements increase trust[182], in addition to compliance with data privacy regulations, such as HIPAA and GDPR, as well as cybersecurity certifications, such as ISO 27001 for data security[202–204].

Sociodemographic factors can affect a patient's trust in a mobile medical system. Systems which are difficult and cumbersome to use can negatively affect a user's confidence in digital health technologies and their effectiveness[205]. Intuitive user interfaces with clear graphics and videos, multilingual support and customer service hotlines for personalized training can increase access and accommodate a range of users[182,206]. Moreover, users can be provided with granular control over data collection, storage and sharing capabilities by enabling opt-in permissions and consent, the ability to delete stored data and explicit requests for data sharing. In addition, real-time privacy indicators, such as status lights when a system is collecting data, can reduce uncertainty about unauthorized recordings[207,208].

Users should also be provided with a channel to report concerns about system performance and shortcomings, such as feedback forms to report false-positive or false-negative results. Periodic software updates to algorithms, models and security architecture can also increase trust and system reliability.

Regulatory considerations

Mobile medical systems face distinct regulatory challenges, including variability in hardware sensors and software application programming interfaces across different models.

Software as a medical device quality management system

The hardware in mobile medical systems is not considered a medical device hardware. The FDA provides regulatory guidance for mobile medical systems that leverage sensors on smart devices. The guidance for mobile medical applications and software as a medical device (including the quality management system and the requirements for production engineering) regulates the custom software application, not the hardware of smart devices, which reduces the costs for regulatory clearance. The FDA has approved mobile medical systems that leverage device sensors, such as microphones and cameras; for example, sonar-based breathing monitors using a smartphone or smart speaker have obtained FDA clearance under software-as-a-medical-device guidelines and via the 510(k) pathway.

According to the medical device academy (a quality and regulatory consulting firm for FDA 510(k) submissions) the cost of human clinical studies, which is required in only 10% of 510(k) submissions, ranges from US$250,000 to US$2.5 million. Simple clinical studies can cost less than US$100,000, whereas for mobile medical apps, which may only consist of software and fall under the software-as-a-medical-device guidelines, the testing costs might be lower.

Calibrating new mobile medical systems

The calibration of a new vision-based mobile medical system can be achieved with colour-calibration cards. For example, the urinalysis app Minuteful Kidney is an FDA-cleared class II medical device that uses a colour-calibration card. Users take a picture of a urinalysis dipstick against a colour-calibration card using a smartphone camera, and computer vision techniques take into account the camera's colour profile and ambient lighting conditions to calibrate the captured image, enabling its application across different smartphone models and operating systems.

External attachments

Mobile health systems that rely on external components — such as 3D-printed parts, paper-based tools requiring user assembly or a colour-calibration card that needs to be printed on paper or displayed on a screen — necessitate a regulatory strategy that determines whether the system is considered a finished or unfinished medical device. Unfinished medical devices introduce variability in the assembly process, which can affect system performance and requires clear instructions and user testing. Alternatively, pre-fabricated and pre-assembled components can be provided to improve reliability and facilitate classification as a finished medical device.

Different operating system versions

Software applications that are built against the Android SDK (version 29 and above, which is supported on Android 10 OS) are designed to be compatible with future versions of Android, as indicated in the Android API documentation. The SDK is designed to isolate applications and extensions to the Android OS, allowing app compatibility with future OS updates. In the case of iOS or other mobile operating systems, calibration procedures may need to be created to ensure that sensor readings can be interpreted across different OS versions and to mitigate the effect of changes to sensor application programming interfaces.

Clinical integration and automated interventions

Integration with the clinical continuum of care

Medical findings obtained by mobile medical systems need to be considered within the context of clinical care by integrating device readouts with medical records to facilitate informed decision-making. However, this requires electronic medical records that allow interoperability and adhere to data standards. For example, formats such as fast healthcare interoperability resources, to transfer data from mobile health systems to electronic health records, enable integration into clinical workflows[209]. Partnerships with public health authorities, healthcare administrators, insurance companies and other key stakeholders may be needed to ensure inclusion of these findings in the medical record. Engaging with insurance companies to ensure a mobile medical test will be reimbursed using an existing or new current procedural terminology code might further promote their integration and adoption[210].

Mobile medical systems could support the initial stages of the continuum of care by enabling the remote screening, diagnosing or monitoring of a medical condition. However, clinical oversight is important to ensure that the test is performed correctly and the result is interpreted within the context of a patient's medical history and demographics, so that guideline-based interventions, personalized treatment plans and rehabilitation and therapy can be implemented appropriately. Therefore, mobile medical devices might not only increase access to healthcare but also aid in timely clinical decision-making without requiring a face-to-face consultation.

Closed-loop systems

Closed-loop systems can interpret measurements and automatically initiate clinical interventions. For example, a fall detection feature on a smart watch uses onboard motion sensors to detect and initiate an alarm if the user has fallen, automatically contacting emergency services and contacts. In a car crash detection feature, motion sensors detect severe car crashes, automatically calling emergency services if the user does not respond to a system-initiated alert. The Pixel Watch 3 includes a loss of pulse detection feature that automatically calls emergency services if the user's heart has stopped beating. Wristbands have been FDA-cleared for the detection of generalized tonic–clonic seizures for patients with epilepsy, alerting caregivers or emergency contacts.

The Apple watch and FitBit watch also have features that do not strictly meet the definition of a closed-loop system, but provide a basic form of clinical interpretation; for example, the irregular heart rhythm feature and ECG app alert the user in the case of rhythms indicating atrial fibrillation, suggesting that a doctor be consulted.

In addition, an active-sonar system can be applied to detect opioid-induced respiratory depression[10] to initiate the injection of naloxone and thus reverse an opioid overdose[211]. Moreover, passive acoustic sensing systems might be applied to detect biomarkers, such as agonal breathing[29], to initiate contact with emergency services that can then perform cardiopulmonary resuscitation.

Outlook

Ensuring that timely in-person appointments with clinicians take place can be difficult in low-resource settings and rural areas. Mobile medical devices might expand access to health assessments. Mobile medical apps that leverage smartphone sensors for health sensing have received FDA clearance, demonstrating that smartphones can be used as a platform for healthcare delivery and to reduce health inequities. In addition, smart speakers, smart watches, wireless earbuds and smart eyewear can be applied to the continuous monitoring of emergent conditions such as cardiac arrests[29] and mental health problems[12,98,123], the ambient monitoring of surgeries and drug preparation in the operating room[25,212], and hearing-loss screening in low- and middle-income countries[23,24].

Various mobile medical systems that rely on built-in sensors of smart devices for health assessments have already passed regulatory clearance or are commercially available. For example, the active sonar technology for smartphones was FDA-cleared in 2021 as a respiratory monitoring app. This technology is also used by the SleepScore app to provide an index of sleep quality. The Pixel 8 Pro smartphone leverages an infrared sensor to measure body temperature at the forehead, and is the first FDA-granted smartphone app for body-temperature monitoring, classified under the 'de novo' category. A smartphone's thermister can also be applied to measure body temperature across different smartphone models[213]. The Google Fit app for Pixel phones relies on computer-vision techniques to measure respiratory rate from the front-facing camera by examining small movements of the chest, as well as heart rate by placing a finger on the rear-facing camera and tracking subtle changes in colour. The Digital Wellbeing app checks coughing and snoring activity using passive acoustic sensing to detect the distinct acoustic fingerprints associated with these body sounds. Sleep sensing algorithms have also been integrated into smart devices. For example, Nest Hub devices leverage mmWave radar to detect an individual's movement, and measures sound, light and temperature to assess sleep quality by machine learning. Fitbit uses the heartbeat and IMU signal to estimate sleep stage. The Apple Watch and Pixel Watch apply motion sensors for car crash detection, fall detection and loss of pulse detection. The Apple Watch and FitBit watch also have an ECG sensor for detecting irregular heart rhythms suggestive of atrial fibrillation. The Samsung Galaxy Watch can measure body composition (body-fat percentage, body-water content, skeletal muscle mass) using bioelectrical impedance analysis. The watch can also measure blood pressure using the onboard PPG sensor. Smart rings, such as the Oura Ring, can monitor heart rate and blood oxygen, and measure body temperature to predict the start of the menstrual period.

In addition, mobile medical systems might have an impact in telemedicine, precision healthcare, long-term health monitoring and disease detection.

Expanded medical tests for telemedicine visits

Healthcare can be made more accessible by increasing the number of medical tests that can be performed remotely through a telemedicine appointment and mobile medical systems[214,215]. For example, mobile medical systems might enable low-cost ultrasound imaging, vital-sign monitoring of a fetus and biofluid testing. However, they require a similar level of accuracy to in-clinic assessments, allow untrained users to perform the test, provide results that are interpretable by both the patient and healthcare provider and protect patient privacy.

Small-data mobile systems for precision healthcare

Machine learning systems for medical diagnostics are typically built on large datasets that should represent the entire population. For example, speech-recognition technology requires training with a variety of words, phrases and accents. However, this would require mobile systems that can be fine-tuned using orders-of-magnitude less data than current systems, for example, by applying few-shot- or zero-shot-based learning methods.

Ambient sensing systems for long-term health monitoring

Smartphones, smart watches and smart speakers might also enable long-term continuous monitoring; for example, ambient monitoring systems can track medical events over time in a contactless manner. Such ambient sensing systems could also be designed to detect recurring events, such as seizures, and to learn from an individual's distinct physiological patterns to become more accurate. In addition, these systems can leverage audible biomarkers to track long-term changes in vocal patterns and measure the progression of cognitive disorders, such as dementia and Alzheimer's disease. However, they need to be privacy-preserving.

Sensors for disease detection

Dogs and insects can smell diseases, such as COVID-19 (ref. 216), diabetes[217] and cancer[218–220]. However, even the best electronic sensors are substantially less sensitive than biological sensing systems. Biomimetic electronic or biohybrid sensors that can detect the presence of disease from gaseous chemical compounds in breath or scent[221], with the help of machine learning algorithms, could be integrated into mobile and non-invasive diagnostic tools, for example, to track the health of individuals in public spaces or to create a real-time barometer of a city's health and track the outbreak of diseases.

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Author contributions
J.C., R.N. and S.G. researched data for the manuscript and contributed to discussion of its contents. J.C. and R.N. wrote the article. M.G. reviewed the manuscript. All authors edited the manuscript.

Competing interests
The authors declare the following competing interests: S.G. and J.C. are co-founders of Wavely Diagnostics, Inc. The remaining authors declare no competing interests.

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