

# Illuminating the dark spaces of healthcare with ambient intelligence

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Advances in machine learning and contactless sensors have given rise to ambient intelligence—physical spaces that are sensitive and responsive to the presence of humans. Here we review how this technology could improve our understanding of the metaphorically dark, unobserved spaces of healthcare. In hospital spaces, early applications could soon enable more efficient clinical workflows and improved patient safety in intensive care units and operating rooms. In daily living spaces, ambient intelligence could prolong the independence of older individuals and improve the management of individuals with a chronic disease by understanding everyday behaviour. Similar to other technologies, transformation into clinical applications at scale must overcome challenges such as rigorous clinical validation, appropriate data privacy and model transparency. Thoughtful use of this technology would enable us to understand the complex interplay between the physical environment and health-critical human behaviours.

Boosted by innovations in data science and artificial intelligence<sup>1,2</sup>, decision-support systems are beginning to help clinicians to correct suboptimal and, in some cases, dangerous diagnostic and treatment decisions<sup>3–5</sup>. By contrast, the translation of better decisions into the physical actions performed by clinicians, patients and families remains largely unassisted<sup>6</sup>. Health-critical activities that occur in physical spaces, including hospitals and private homes, remain obscure. To gain the full dividends of medical advancements requires—in part—that affordable, human-centred approaches are continuously highlighted to assist clinicians in these metaphorically dark spaces.

Despite numerous improvement initiatives, such as surgical safety checklists<sup>7</sup>, by the National Institutes of Health (NIH), Centres for Disease Control and Prevention (CDC), World Health Organization (WHO) and private organizations, as many as 400,000 people die every year in the United States owing to lapses and defects in clinical decision-making and physical actions<sup>8</sup>. Similar preventable suffering occurs in other countries, as well-motivated clinicians struggle with the rapidly growing complexity of modern healthcare<sup>9,10</sup>. To avoid overwhelming the cognitive capabilities of clinicians, advances in artificial intelligence hold the promise of assisting clinicians, not only with clinical decisions but also with the physical steps of clinical decisions<sup>6</sup>.

Advances in machine learning and low-cost sensors can complement existing clinical decision-support systems by providing a computer-assisted understanding of the physical activities of healthcare. Passive, contactless sensors (Fig. 1) embedded in the environment can form an ambient intelligence that is aware of people's movements and adapt to their continuing health needs<sup>11–14</sup>. Similar to modern driver-assistance systems, this form of ambient intelligence can help clinicians and in-home caregivers to perfect the physical motions that comprise the final steps of modern healthcare. Already enabling better manufacturing, safer autonomous vehicles and smarter sports entertainment<sup>15</sup>, clinical physical-action support can more reliably translate

the rapid flow of biomedical discoveries into error-free healthcare delivery and worldwide human benefits.

This Review explores how ambient, contactless sensors, in addition to contact-based wearable devices, can illuminate two health-critical environments: hospitals and daily living spaces. With several illustrative clinical-use cases, we review recent algorithmic research and clinical validation studies, citing key patient outcomes and technical challenges. We conclude with a discussion of broader social and ethical considerations including privacy, fairness, transparency and ethics. Additional references can be found in Supplementary Note 1.

## Hospital spaces


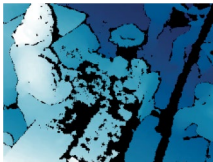

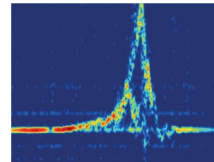
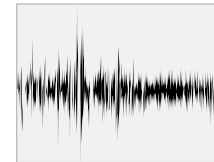
In 2018, approximately 7.4% of the US population required an overnight hospital stay<sup>16</sup>. In the same year, 17 million admission episodes were reported by the National Health Service (NHS) in the UK<sup>17</sup>. Yet, healthcare workers are often overworked, and hospitals understaffed and resource-limited<sup>18,19</sup>. We discuss a number of hospital spaces in which ambient intelligence may have an important role in improving the quality of healthcare delivery, the productivity of clinicians, and business operations (Fig. 2). These improvements could be of great assistance during healthcare crises, such as pandemics, during which time hospitals encounter a surge of patients<sup>20</sup>.

## Intensive care units

Intensive care units (ICUs) are specialized hospital departments in which patients with life-threatening illnesses or critical organ failures are treated. In the United States, ICUs cost the health system US\$108 billion per year<sup>21</sup> and account for up to 13% of all hospital costs<sup>22</sup>.

One promising use case of ambient intelligence in ICUs is the computer-assisted monitoring of patient mobilization. ICU-acquired weaknesses are a common neuromuscular impairment in critically ill

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	Camera	Depth sensor	Thermal sensor	Radio sensor	Acoustic sensor
Sensory information	RGB, colour, video	Lidar	Infrared	Radar, Wi-Fi	Microphone
Function	Measures colour (visible light)	Measures distance to objects	Measures surface temperature	Estimates distance and velocity	Measures air pressure waves (sound)
Sampling rate	30 Hz (1,920 × 1,080)	30 Hz (1,280 × 720)	10 Hz (640 × 480)	800 Hz	44.1 kHz
Bit depth	24 bits	16 bits	16 bits	32 bits	16 bits
Uses	Object recognition, person detection	3D object detection, robotic navigation	Night vision, equipment safety	Motion detection, object detection	Speech recognition, event detection
Data visualization					

**Fig. 1 | Contactless sensors for ambient intelligence.** Brightly coloured pixels denote objects that are closer to the depth sensor. Black pixels denote sensor noise caused by reflective, metallic objects. The radio sensor shows a micro-Doppler signature of a moving object, for which the *x* axis denotes

time (5 s) and the *y* axis denotes the Doppler frequency. The radio sensor image is reproduced from ref.<sup>89</sup>. The acoustic sensor displays an audio waveform of a person speaking, for which the *x* axis denotes time (5 s) and the *y* axis denotes the signal amplitude.

patients, potentially leading to a twofold increase in one-year mortality rate and 30% higher hospital costs<sup>23</sup>. Early patient mobilization could reduce the relative incidence of ICU-acquired weaknesses by 40%<sup>24</sup>. Currently, the standard mobility assessment is through direct, in-person observation, although its use is limited by cost impracticality, observer bias and human error<sup>25</sup>. Proper measurement requires a nuanced understanding of patient movements<sup>26</sup>. For example, localized wearable devices can detect pre-ambulation manoeuvres (for example, the transition from sitting to standing)<sup>27</sup>, but are unable to detect external assistance or interactions with the physical space (for example, sitting on chair versus bed)<sup>27</sup>. Contactless, ambient sensors could provide the continuous and nuanced understanding needed to accurately measure patient mobility in ICUs.

In one pioneering study, researchers installed ambient sensors (Fig. 2a) in one ICU room (Fig. 2b) and collected 362 h of data from eight patients<sup>28</sup>. A machine-learning algorithm categorized in-bed, out-of-bed and walking activities with an accuracy of 87% when compared to retrospective review by three physicians. In a larger study at a different hospital (Fig. 2c), another research team installed depth sensors in eight ICU rooms<sup>29</sup>. They trained a convolutional neural network<sup>1</sup> on 379 videos to categorize mobility activities into four categories (Fig. 2d). When validated on an out-of-sample dataset of 184 videos, the algorithm demonstrated 87% sensitivity and 89% specificity. Although these preliminary results are promising, a more insightful evaluation could provide stratified results rather than aggregate performance on short, isolated video clips. For example, one study used cameras, microphones and accelerometers to monitor 22 patients in ICUs, with and without delirium, over 7 days<sup>30</sup>. The study found significantly fewer head motions of patients who were delirious compared with patients who were not. Future studies could leverage this technology to detect delirium sooner and provide researchers with a deeper understanding of how patient mobilization affects mortality, length of stay and patient recovery.

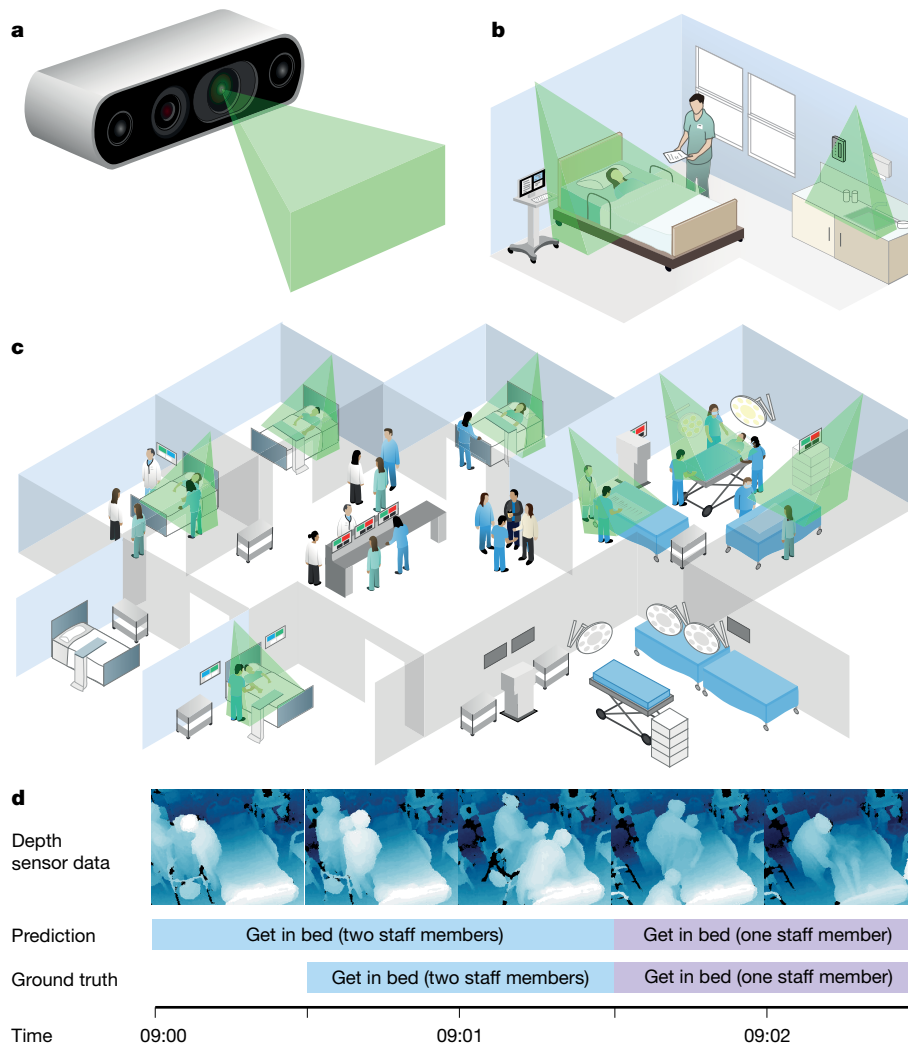
Another early application is the control of hospital infections. Worldwide, more than 100 million patients are affected by hospital-acquired (that is, nosocomial) infections each year<sup>31</sup>, with up to 30% of patients in ICUs experiencing a nosocomial infection<sup>32</sup>. Proper compliance with hand hygiene protocols is one of the most effective methods of reducing the frequency of nosocomial infections<sup>33</sup>. However, measuring compliance remains challenging. Currently, hospitals rely on auditors to measure compliance, despite being expensive, non-continuous and biased<sup>34</sup>. Wearable devices, particularly radio-frequency identification (RFID) badges, are a potential solution. Unfortunately, RFID provides

coarse location estimates (that is, within tens of centimetres<sup>35</sup>), making it unable to categorize fine-grained movements such as the WHO's five moments of hand hygiene<sup>36</sup>. Alternatively, ambient sensors could monitor handwashing activities with higher fidelity—differentiating true use of an alcohol-gel dispenser from a clinician walking near a dispenser. In a pioneering study, researchers installed depth sensors above wall-mounted dispensers across an entire hospital unit<sup>37,38</sup>. A deep-learning algorithm achieved an accuracy of 75% at measuring compliance for 351 handwashing events during one hour. During the same time period, an in-person observer was 63% accurate, while a proximity algorithm (for example, RFID) was only 18% accurate. In more nuanced studies, ambient intelligence detected the use of contact-precautions equipment<sup>39</sup> and physical contact with the patient<sup>40</sup>. A critical next step is to translate ambient observation into changes in clinical behaviour, with a goal of improving patient outcomes.

### Operating rooms

Worldwide, more than 230 million surgical procedures are undertaken annually<sup>41</sup> with up to 14% of patients experiencing an adverse event<sup>42</sup>. This percentage could be reduced through quicker surgical feedback, such as more frequent coaching of technical skill, which could reduce the number of errors by 50%<sup>43</sup>. Currently, the skills of a surgeon are assessed by peers and supervisors<sup>44</sup>, despite being time-consuming, infrequent and subjective. Wearable sensors can be attached to hands or instruments to estimate the surgeon's skills<sup>45</sup>, but may inhibit hand dexterity or introduce sterilization complexity. Ambient cameras are an unobtrusive alternative<sup>46</sup>. One study trained a convolutional neural network<sup>1</sup> to track a needle driver in prostatectomy videos<sup>47</sup>. Using peer-evaluation as the reference standard, the algorithm categorized 12 surgeons into high- and low-skill groups with an accuracy of 92%. A different study used videos from ten cholecystectomy procedures to reconstruct the trajectories of instruments during surgery and linked them to technical ratings by expert surgeons<sup>48</sup>. Further studies, such as video-based surgical phase recognition<sup>49</sup>, could potentially lead to improved surgical training. However, additional clinical validation is needed and appropriate feedback mechanisms must be tested.

In the operating room, ambient intelligence is not limited to endoscopic videos<sup>50</sup>. Another example is the surgical count—a process of counting used objects to prevent objects being accidentally retained inside the patient<sup>51</sup>. Currently, dedicated staff time and effort are required to visually and verbally count these objects. Owing to attention deficit and insufficient team communication<sup>52</sup>, it is possible for the human-adjudicated count to incorrectly label an object as returned



**Fig. 2 | Ambient intelligence for hospitals.** **a**, Commercial ambient sensor for which the coverage area is shown in green (that is, the field of view of visual sensors and range for acoustic and radio sensors). **b**, Sensors deployed inside a patient room can capture conversations and the physical motions of patients, clinicians and visitors. **c**, Sensors can be deployed throughout a hospital.

**d**, Comparison of predictions and ground truth of activity from depth sensor data. Top, data from a depth sensor. Middle, the prediction of the algorithm of mobilization activity, duration and the number of staff who assist the patient. Bottom, human-annotated ground truth from a retrospective video review. **d**, Adapted from ref. 29.

when it is actually missing<sup>51</sup>. Automated counting systems, in particular, could assist surgical teams<sup>53</sup>. One study showed that barcode-equipped laparotomy sponges reduced the retained object rate from once every 16 days to once every 69 days<sup>54</sup>. Similar results were found with RFID and Raytec sponges<sup>55</sup>. However, owing to their size, barcodes and RFID cannot be applied to needles and instruments, which are responsible for up to 55% of counting discrepancies<sup>51</sup>—each discrepancy delaying the case by 13 min on average<sup>51</sup>. In addition to sponges, ambient cameras could count these smaller objects and potentially staff members<sup>56</sup>. In one operating room, researchers used ceiling-mounted cameras to track body parts of surgical team members with errors as low as five centimetres<sup>57</sup>. Ambient data collected throughout the room could create fine-grained logs of intraoperative activity<sup>58</sup>. Although these studies are promising as a proof of concept, further research needs to quantify the impact on patient outcomes, reimbursement and efficiency gains.

### Other healthcare spaces

Clinicians spend up to 35% of their time on medical documentation tasks<sup>59</sup>, taking valuable time away from patients. Currently, physicians perform documentation during or after each patient visit. Some providers use medical scribes to alleviate this burden, resulting in 0.17 more patients seen per hour and 0.21 more relative value units per patient

(that is, insurer reimbursement)<sup>60</sup>. However, scribes are expensive to train and have high turnover<sup>61</sup>. Ambient microphones could perform a similar task to that of medical scribes<sup>62</sup>. Medical dictation software is an alternative, but is traditionally limited to the post-visit report<sup>63</sup>. In one study, researchers trained a deep-learning model on 14,000 h of outpatient audio from 90,000 conversations between patients and physicians<sup>64</sup>. The model demonstrated a word-level transcription accuracy of 80%, suggesting it may be better than the 76% accuracy of medical scribes<sup>65</sup>. In terms of clinical utility, one medical provider found that microphones attached to eyeglasses reduced time spent on documentation from 2 h to 15 min and doubled the time spent with patients<sup>62</sup>.

From a management standpoint, ambient intelligence can improve the transition to activity-based costing<sup>66</sup>. Traditionally, insurance companies and hospital administrators estimated health outcomes per US dollar spent through a top-down approach of value-based accounting<sup>67</sup>. Time-driven activity-based costing is a bottom-up alternative and estimates the costs by individual resource time and cost (for example, the use of an ICU ventilator for 48 h)<sup>68</sup>. This can better inform process redesigns<sup>66</sup>—which, for one provider, led to 19% more patient visits with 17% fewer employees, without degradation of the patient outcomes<sup>69</sup>. Currently, in-person observations, staff interviews and electronic health records are used to map clinical activities to costs<sup>68</sup>. As described in

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this Review, ambient intelligence can automatically recognize clinical activities<sup>70</sup>, count healthcare personnel<sup>29</sup> and estimate the duration of activities<sup>29</sup> (Fig. 2d). However, evidence of the clinical benefits of ambient intelligence is currently lacking, as the paradigm of activity-based costing is relatively new to hospital staff. As the technology develops, we hope that hospital administrators participate in the implementation and validation of ambient activity-based costing systems.

### Daily living spaces

Humans spend a considerable portion of time at home. Around the world, the population is ageing<sup>71</sup>. Not only will this increase the amount of time spent at home, but it will also increase the importance of independent living, chronic disease management, physical rehabilitation and mental health of older individuals in daily living spaces.

### Elderly living spaces and ageing

By 2050, the world's population aged 65 years or older will increase from 700 million to 1.5 billion<sup>71</sup>. Activities of daily living (ADLs), such as bathing, dressing and eating, are critical to the well-being and independence of this population. Impairment of one's ability to perform ADLs is associated with a twofold increase in falling risk<sup>72</sup> and up to a fivefold increase in one-year mortality rate<sup>73</sup>. Earlier detection of impairments could provide an opportunity to provide timely clinical care<sup>11</sup>, potentially improving the ability to perform ADL by a factor of two<sup>74</sup>. Currently, ADLs are measured through self-reported questionnaires or manual grading by caregivers, despite the fact that these measurements are infrequent, biased and subjective<sup>75</sup>. Alternatively, wearable devices (such as accelerometers or electrocardiogram sensors) can track not only ADLs, but also heart rate, glucose level and respiration rate<sup>76</sup>. However, wearable devices are unable to discern whether a patient received ADL assistance—a key component of ADL evaluations<sup>77</sup>. Contactless, ambient sensors (Fig. 3a) could potentially identify these clinical nuances while detecting a greater range of activities<sup>78</sup>.

In one of the first studies of its kind, researchers installed a depth and thermal sensor (Fig. 3b) inside the bedroom of an older individual and observed 1,690 activities during 1 month, including 231 instances of caregiver assistance<sup>79</sup> (Fig. 3c). A convolutional neural network<sup>1</sup> was 86% accurate at detecting assistance. In a different study, researchers collected ten days of video from six individuals in an elderly home and achieved similar results<sup>80</sup>. Although visual sensors are promising, they raise privacy concerns in some environments, such as bathrooms, which is where grooming, bathing and toileting activities occur, all of which are strongly indicative of cognitive function<sup>81</sup>. This led researchers to explore acoustic<sup>82</sup> and radar sensors<sup>83</sup>. One study used microphones to detect showering and toileting activities with accuracies of 93% and 91%, respectively<sup>82</sup>. However, a limitation of these studies is their evaluation in a small number of environments. Daily living spaces are highly variable, thus introducing generalization challenges. Additionally, privacy is of utmost importance. Development and verification of secure, privacy-safe systems is essential if this technology is to illuminate daily living spaces.

Another application for the independent living of older individuals is fall detection<sup>84</sup>. Approximately 29% of community-dwelling adults fall at least once a year<sup>85</sup>. Laying on the floor for more than one hour after a fall is correlated with a fivefold increase in 12-month mortality<sup>86</sup>. Furthermore, the fear of falling—associated with depression and lower quality of life<sup>87</sup>—can be reduced due to the perceived safety benefit of fall-detection systems<sup>88</sup>. For decades, researchers developed fall-detection systems with wearable devices and contactless ambient sensors<sup>89</sup>. A systematic review found that wearable devices detected falls with 96% accuracy while ambient sensors were 97% accurate<sup>90</sup>. In a different study, researchers installed Bluetooth (that is, radio) beacons in 271 homes<sup>91</sup>. Using signal strengths from each beacon, a machine-learning algorithm categorized the frailty of older individuals

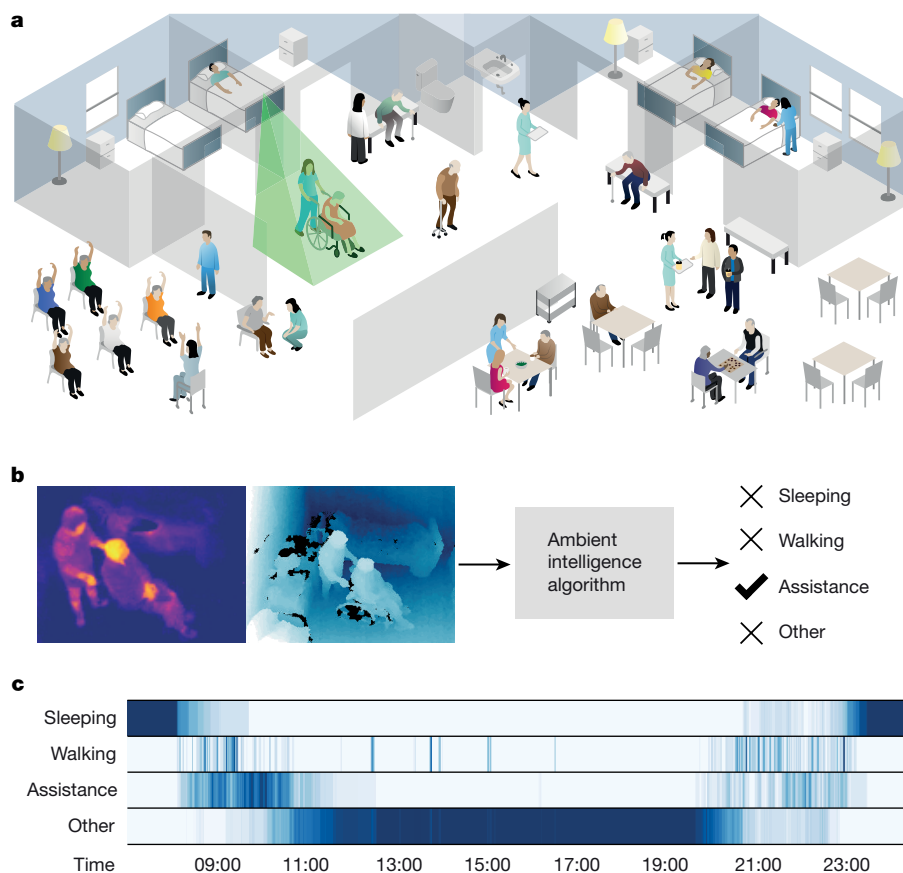
with an accuracy of 98%. In another study, researchers installed depth and radar sensors on the ceiling of 16 senior living apartments for 2 years<sup>92</sup>. Radar signals, transformed by a wavelet decomposition, detected 100% of falls with fewer than two false alarms per day<sup>93</sup>. Depth sensors produced one false alarm per month with a fall detection rate of 98%<sup>94</sup>. The ambient sensors were sufficiently fast (that is, low latency) to provide real-time email alerts to caregivers at 13 assisted-living communities<sup>95</sup>. Compared to a control group of 85 older individuals over 1 year, the real-time intervention significantly slowed the functional decline of 86 older individuals. When combined with wearable devices, one study found that the fall-detection accuracy of depth sensors increased from 90% to 98%<sup>96</sup>, suggesting potential synergies between contactless and wearable sensors. As ambient intelligence begins to bridge the gap between observation and intervention, further studies are needed to explore regulatory approval processes, legal implications and ethical considerations.

### Chronic disease management

With applications to physical rehabilitation and chronic diseases, gait analysis is an important tool for diagnostic testing and measuring treatment efficacy<sup>97</sup>. For example, frequent and accurate gait analysis could improve postoperative health for children with cerebral palsy<sup>98</sup> or enable earlier detection of Parkinson's disease by up to 4 years<sup>99</sup>. Traditionally limited to research laboratories with force plates and motion capture systems<sup>100</sup>, gait analysis is being increasingly conducted with wearable devices<sup>101</sup>. One study used accelerometers to estimate the clinical-standard 6-min walking distance of 30 patients with chronic lung disease<sup>102</sup>. The study found an average absolute error rate of 6%. One limitation is that wearables must be physically attached to the body, making them inconvenient for patients<sup>103</sup>. Alternatively, contactless sensors could continuously measure gait with improved fidelity and create interactive, home-based rehabilitation programmes<sup>104</sup>. Several studies measured gait in natural settings with cameras<sup>105</sup>, depth sensors<sup>104</sup>, radar<sup>106</sup> and microphones<sup>107</sup>. One study used depth sensors to measure gait patterns of nine patients with Parkinson's disease<sup>108</sup>. Using a high-end motion capture system as the ground truth, the study found that depth sensors could track vertical knee motions to within four centimetres. Another study used depth sensors to create an exercise game for patients with cerebral palsy<sup>109</sup>. Over the course of 24 weeks, patients using the game improved their balance and gait by 18% according to the Tinetti test<sup>110</sup>. Although promising, these studies evaluated a single sensor modality. In laboratory experiments, gait detection improved by 3% to 7% when microphones were combined with wearable sensors<sup>111</sup>. When feasible, studies could investigate potential synergies of multiple sensing modalities (such as passive infrared motion sensors, contact sensors and wearable cameras).

### Mental health

Mental illnesses, such as depression, anxiety and bipolar disorder, affect 43 million adults in the USA<sup>112</sup> and 165 million people in the European Union<sup>113</sup>. It is estimated that 56% of adults with mental illnesses do not seek treatment owing to barriers such as financial cost and provider availability<sup>112</sup>. Currently, self-reported questionnaires and clinical evaluations (for example, the Diagnostic and Statistical Manual of Mental Disorders (DSM-5)) are the standard tool for identifying symptoms of mental illness, despite being infrequent and biased<sup>114</sup>. Alternatively, ambient sensors could provide continuous and cost-effective symptom screening<sup>115</sup>. In one study, researchers collected audio, video and depth data from 69 individuals during 30-min, semi-structured clinical interviews<sup>116</sup>. Using the patient's verbal cues and upper body movement, a machine-learning algorithm detected 46 patients with schizophrenia with a positive predictive value of 95% and sensitivity of 84%. Similarly, in an emergency department, natural language analysis of clinical interviews with 61 adolescent individuals, of whom 31 were suicidal, yielded a model capable of categorizing patients who were suicidal with 90%



**Fig. 3 | Ambient intelligence for daily living spaces.** **a**, Elderly home equipped with one ambient sensor. The green frustum indicates the coverage area of the sensor (that is, the field of view for visual sensors and range for acoustic and radio sensors). **b**, Thermal and depth data from the sensor are processed by an

ambient intelligence algorithm for activity categorization. **c**, Summary of a patient's activities for a single day. Darker blue sections indicate more frequent activity. **c**, Adapted from ref. <sup>79</sup>.

accuracy<sup>117</sup>. Although impressive, further trials are needed to validate the effect on patient outcomes.

However, even after detection, treating mental health illnesses remains complex. Idiosyncratic therapist effects can cause up to 17% of the variance in outcomes<sup>118</sup>, making it difficult to conduct psychotherapy research. Transcripts are the standard method for identifying features of good therapy<sup>119</sup>, but are expensive to collect. Manual coding of a 20-min session can range from 85 to 120 min<sup>120</sup>. Ambient sensors could provide cheaper, higher-quality transcripts for psychotherapy research. Using text messages of treatment sessions, one study used a recurrent neural network<sup>1</sup> to detect instances of 24 therapist techniques from 14,899 patients<sup>121</sup>. The study identified several techniques correlated with improved Patient Health Questionnaire (PHQ-9) and General Anxiety Disorder (GAD-7) scores. A different study used microphones and a speech-recognition algorithm to transcribe and estimate therapists' empathy from 200 twenty-minute motivational interviewing sessions<sup>120</sup>. Using a committee of human assessors as the gold standard, the algorithm was 82% accurate. Although this is lower than the 90% accuracy of a single human assessor<sup>120</sup>, ambient intelligence can more readily be applied to a larger number of patients. Using ambient intelligence, researchers can now conduct large-scale studies to reaffirm their understanding of psychotherapy frameworks. However, further research is needed to validate the generalization of these systems to a diverse population of therapists and patients.

### Technical challenges and opportunities

Ambient intelligence can potentially illuminate the healthcare delivery process by observing recovery-related behaviours, reducing

unintended clinician errors, assisting the ageing population and monitoring patients with chronic diseases. In Table 1, we highlight seven technical challenges and opportunities related to the recognition of human behaviour in complex scenes and learning from big data and rare events in clinical settings.

### Behaviour recognition in complex scenes

Understanding complex human behaviours in healthcare spaces requires research that spans multiple areas of machine intelligence such as visual tracking, human pose estimation and human-object interaction models. Consider morning rounds in a hospital. Up to a dozen clinicians systematically review and visit each patient in a hospital unit. During this period, clinicians may occlude a sensor's view of the patient, potentially allowing health-critical activities to go undetected. If an object is moving before occlusion, tracking algorithms (Table 1) can estimate the position of the object while occluded<sup>122</sup>. For longer occlusions, matrix completion methods, such as image inpainting, can 'fill in' what is behind the occluding object<sup>123</sup>. Similar techniques can be used to denoise audio in spectrogram form<sup>124</sup>. If there are no occlusions, the next step is to locate people. During morning rounds, clinicians may hand each other objects or point across the room, introducing multiple layers of body parts from the perspective of the sensor. Human pose-estimation algorithms (Table 1) attempt to resolve this ambiguity by precisely locating body parts and assigning them to the correct individuals<sup>125</sup>. Building highly accurate human behaviour models is needed for ambient intelligence to succeed in complex clinical environments.

Ambient intelligence needs to understand how humans interact with objects and other people. One class of methods attempts to identify visually grounded relationships in images<sup>126</sup>, commonly in the form of

**Table 1 | Algorithmic challenges**

Challenge	Sub-challenge	Technical approaches	ICUs		Operating rooms		Other		Elderly care		Chronic	Mental health	
			Patient mobility	Hand hygiene	Skills	Surgical count	Notes	Costing	ADLs	Falls	Gait analysis	Symptom screening	Therapy research
Behaviour recognition in complex scenes	Complex environments	Visual tracking, matrix completion	x	x	x	x	-	x	x	x	x	x	-
	Locating multiple humans	Pedestrian detection, human pose estimation	x	-	-	-	-	x	x	x	x	-	-
	Recognizing human behaviours	Scene graphs, activity recognition	x	x	-	x	-	x	x	x	-	-	x
Learning with big data and rare events	Big data	Distributed learning, optimizers	x	x	x	x	x	x	x	x	x	x	x
	Real-time detections	Two-stage models, model compression	-	x	x	x	-	-	-	x	-	-	-
	Rare events	Calibration, loss weighting	x	-	-	x	-	-	-	x	-	x	-
	Generalization to new environments	Transfer learning, few-shot learning	x	x	x	x	x	x	x	x	x	x	x

Rows denote algorithmic challenges. Columns denote clinical-use cases. Challenges applicable to specific clinical-use cases are marked by an 'x'. 'Skills' indicates the evaluation of surgical skills; 'notes' refers to medical documentation.

a scene graph (Table 1). A scene graph is a network of interconnected nodes, in which each node represents an object in the image and each connection represents their relationship<sup>127</sup>. Not only can scene graphs aid in the recognition of human behaviour, but they could also make ambient intelligence more transparent<sup>128</sup>.

### Learning from big data and rare events

Ambient sensors will produce petabytes of data from hospitals and homes<sup>129</sup>. This requires new machine-learning methods that are capable of modelling rare events and handling big data to be developed (Table 1). Large-scale activity-understanding models could require days to train unless large clusters of specialized hardware are used<sup>130</sup>. Cloud servers are a potential solution, but can be expensive as ambient intelligence may require considerable storage, computation and network bandwidth. Improved gradient-based optimizers<sup>131</sup> and neural network architectures<sup>132</sup> can potentially reduce training time. However, quickly training a model does not guarantee it will be fast during inference (that is, real-time detections) (Table 1). For example, video-based activity recognition models are slow, typically on the order of 1 to 10 frames per second<sup>133</sup>. Even optimized models capable of 100 frames per second<sup>134</sup> may have difficulties processing terabytes of data each day. Techniques such as model compression<sup>135</sup> and quantization<sup>136</sup> can reduce storage and computational requirements. Instead of processing audio or video at full spatial or temporal resolution, some methods quickly identify segments of interest, known as proposals<sup>137</sup>. These proposals are then provided to heavy-duty modules for highly accurate but computation-intensive activity recognition.

Although the volume of data produced by ambient sensors is large, some clinical events are rare and infrequent (Table 1). The detection of these long-tail events is necessary to understand health-critical behaviours. Consider the example of fall detection. The majority of ambient data contains normal activity, biasing the algorithm owing to label imbalance. More broadly, statistical bias can apply to any category of data, such as protected class attributes<sup>138</sup>. One solution is to statistically calibrate the algorithm, resulting in consistent error rates across specified attributes<sup>139</sup>. However, some healthcare environments may

have a greater incidence of falls than in the original training set. This requires generalization (Table 1): the ability of an algorithm to operate on unseen distributions<sup>140</sup>. Instead of training a model designed for all distributions, one alternative is to take an existing model and fine-tune it on the new distribution<sup>141</sup>—also known as transfer learning<sup>142</sup>. Another solution, domain adaptation<sup>143</sup>, attempts to minimize the gap between the training and testing distributions, often through better feature representations. For low-resource healthcare providers, few-shot learning—algorithms capable of learning from as few as one or two examples<sup>144</sup>—could be used.



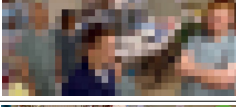


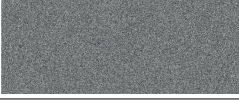
### Social and ethical considerations

Trustworthiness of ambient intelligence systems is critical to achieve the potential of this technology. Although there is an increasing body of literature on trustworthy artificial intelligence<sup>145</sup>, we consider four separate dimensions of trustworthiness: privacy, fairness, transparency and research ethics. Developing the technology while addressing all four factors requires close collaborations between experts from medicine, computer science, law, ethics and public policy.

### Privacy

Ambient sensors, by design, continuously observe the environment and can uncover new information about how physical human behaviours influence the delivery of healthcare. For example, sensors can measure vital signs from a distance<sup>146</sup>. While convenient, such knowledge could potentially be used to infer private medical conditions. As citizens worldwide are becoming more sensitive to mass data collection, there are growing concerns over confidentiality, sharing and retention of this information<sup>147</sup>. It is therefore essential to co-develop this technology with privacy and security in mind, not only in terms of the technology itself but also in terms of a continuous involvement of all stakeholders during the development<sup>148</sup>.

A number of existing and emerging privacy-preserving techniques are presented in Fig. 4. One method is to de-identify data by removing the identities of the individuals. Another method is data minimization,

Method	Description	Computing hardware	Transformed result
Differential privacy	Adds noise to the data; minimally affects population-level analysis	Edge computer	
Face blurring	Detects and blurs human faces	Sensor, edge computer	
Dimensionality reduction	Reduces the input size by reducing the number of features	Sensor, edge computer	
Body masking	Replaces people with faceless avatars	Edge computer	
Federated learning	Edge devices learn locally, then sends gradient updates to central server	Edge computer, centralized server	
Homomorphic encryption	Enables predictions to be made from encrypted data	Edge computer, centralized server	

**Fig. 4 | Computational methods to protect privacy.** There is a trade-off between the level of privacy protection provided by each method and the required computational resources. The methods used to generate the transformed images are described in detail elsewhere: differential privacy, ref. <sup>166</sup>; dimensionality reduction, ref. <sup>167</sup>; body masking, ref. <sup>168</sup>; federated learning, ref. <sup>169</sup>; homomorphic encryption, ref. <sup>170</sup>. The original image was produced by S. McCoy and has previously been published<sup>171</sup>. The appearance of US Department of Defence visual information does not imply or constitute endorsement by the US Department of Defence.

which minimizes data capture, transport and human bycatch. An ambient system could pause when a hospital room is unoccupied by a patient. However, even if data are de-identified, it may be possible to re-identify an individual<sup>149</sup>. Super-resolution techniques<sup>150</sup> can partially reverse the effects of face blurring and dimensionality reduction techniques, potentially enabling re-identification. This suggests that data should remain on-device to reduce the risk of unauthorized access and re-identification.

Legal and social complexities will inevitably arise. There are documented examples in which companies were required to provide data from ambient speakers and cameras to law enforcement<sup>151</sup>. Although these devices were located inside potential crime scenes, this raises the question at what point incidental findings outside the crime scene, such as inadvertent confessions, should be disclosed. Related to data sharing, some healthcare organizations have shared patient information with third parties such as data brokers<sup>152</sup>. To mitigate this, patients should proactively request healthcare providers to use privacy-preserving practices (Fig. 4). Additionally, clinicians and technologists must collaborate with critical stakeholders (for example, patients, family or caregivers), legal experts and policymakers to develop governance frameworks for ambient systems.

## Fairness

Ambient intelligence will interact with large patient populations, potentially several orders of magnitude larger than the reach of current clinicians. This compels us to scrutinize the fairness of ambient systems. Fairness is a complex and multi-faceted topic, discussed by multiple research communities<sup>138</sup>. We highlight here two aspects of algorithmic fairness as examples: dataset bias and model performance.

Labelled datasets are the foundation of most machine-learning systems<sup>1</sup>. However, medical datasets have been biased, even before deep learning<sup>153</sup>. These biases can adversely affect clinical outcomes for certain populations<sup>154</sup>. If an individual is missing specific attributes, whether owing to data-collection constraints or societal factors, algorithms could misinterpret their entire record, resulting in higher levels of predictive error<sup>155</sup>. One method for identifying bias is to analyse model performance across different groups<sup>156</sup>. In one study, error rates varied across ethnic groups when predicting 30-day psychiatric readmission rates<sup>157</sup>. A more rigorous method could test for equal sensitivity and equal positive-predictive value. However, equal model performance may not produce equal clinical outcomes, as some populations may have inherent physiological differences. Nonetheless, progress is being made to mitigate bias, such as the PROBAST tool<sup>158</sup>.

## Transparency

Ambient intelligence can uncover insights about how healthcare delivery is influenced by human behaviour. These discoveries may surprise some researchers, in which case, clinicians and patients need to trust the findings before using them. Instead of opaque, black-box models, ambient intelligence systems should provide interpretable results that are predictive, descriptive and relevant<sup>159</sup>. This can aid in the challenging task of acquiring stakeholder buy-in, as technical illiteracy and model opacity can stagnate efforts to use ambient intelligence in healthcare<sup>160</sup>. Transparency is not limited to the algorithm. Dataset transparency—a detailed trace of how a dataset was designed, collected and annotated—would allow for specific precautions to be taken for future applications, such as training human annotators or revising the inclusion and exclusion criteria of a study. Formal guidelines on transparency, such as the TRIPOD statement<sup>161</sup>, are actively being developed. Another tool is the use of model cards<sup>162</sup>, which are short analyses that benchmark the algorithm across different populations and outline evaluation procedures.

## Research ethics

Ethical research encompasses topics such as the protection of human participants, independent review and public beneficence. The Belmont Report, which prompted the regulation of research involving human participants, includes ‘respect for persons’ as a fundamental principle. In research, this manifests as informed consent from research participants. However, some regulations allow research to occur without consent if the research poses minimal risks to participants or if it is infeasible to obtain consent. For large-scale ambient intelligence studies, obtaining informed consent can be difficult, and it may in some cases be impossible due to automatic de-identification techniques (Fig. 4). In these cases, public engagement or deliberative democracy can be alternative solutions<sup>163</sup>.

Relying solely on the integrity of principal investigators to conduct ethical research may introduce potential conflicts of interest. To mitigate this risk, academic research that involves human participants requires the approval from an Institutional Review Board. Public health surveillance, intended to prevent widespread disease and improve health, does not require independent review<sup>164</sup>. Depending on the application, ambient intelligence could be classified as either<sup>165</sup>. Researchers are urged to consult with experts from law and ethics to determine appropriate steps for protecting all human participants while maximizing public beneficence.

## Summary

Centuries of medical practice led to a knowledge explosion, fuelling unprecedented advances in human health. Breakthroughs in artificial intelligence and low-cost, contactless sensors have given rise to an ambient intelligence that can potentially improve the physical execution of healthcare delivery. Preliminary results from hospitals and

daily living spaces confirm the richness of information gained through ambient sensing. This extraordinary opportunity to illuminate the dark spaces of healthcare requires computer scientists, clinicians and medical researchers to work closely with experts from law, ethics and public policy to create trustworthy ambient intelligence systems for healthcare.

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