nature research

https://doi.org/10.1038/s41586-020-2669-y

Supplementary information

Illuminating the dark spaces of healthcare with ambient intelligence

In the format provided by the authors and unedited

Supplementary Note 1

A. Background

These references provide additional background reading on medical errors and includes citations to early works on ambient intelligence in healthcare.

171. Institute of Medicine & Committee on Quality of Health Care in America. *To Err Is Human: Building a Safer Health System*. (National Academies Press, 2000).
172. Rotmensch, M., Halpern, Y., Tlimat, A., Horng, S. & Sontag, D. Learning a Health Knowledge Graph from Electronic Medical Records. *Sci. Rep.* **7**, 5994 (2017).
173. Giraldo, P. *et al.* A retrospective review of medical errors adjudicated in court between 2002 and 2012 in Spain. *Int. J. Qual. Health Care* **28**, 33–39 (2016).
174. Morimoto, T. *et al.* Incidence of adverse drug events and medication errors in Japan: the JADE study. *J. Gen. Intern. Med.* **26**, 148–153 (2011).
175. Wilson, R. M. *et al.* The Quality in Australian Health Care Study. *Med. J. Aust.* **163**, 458–471 (1995).
176. Corchado, J. M., Bajo, J. & Abraham, A. GerAmi: Improving Healthcare Delivery in Geriatric Residences. *IEEE Intell. Syst.* **23**, 19–25 (2008).
177. Dey, N. & Ashour, A. S. Ambient Intelligence in healthcare: a state-of-the-art. *Global Journal of Computer Science and Technology* **17**, 19–28 (2017).
178. Ramos, C., Augusto, J. C. & Shapiro, D. Ambient Intelligence—the Next Step for Artificial Intelligence. *IEEE Intell. Syst.* **23**, 15–18 (2008).

B. Hospital Spaces

In this section, references elaborate on the clinical problems in intensive care units, operating rooms, and other healthcare spaces. This includes review articles which outline the problem and clinical trials which investigate potential technological and non-technological solutions.

179. Maruyama, T. Depressive symptoms and overwork among physicians employed at a university hospital in Japan. *J Health Soc Sci* **2**, 243–256 (2017).
180. Yang, T. *et al.* Job Stress and Presenteeism among Chinese Healthcare Workers: The Mediating Effects of Affective Commitment. *Int. J. Environ. Res. Public Health* **14**, 978 (2017).

B.1. Intensive Care Units

References in this subsection focus investigate how patient mobilization affects ICU-acquired weaknesses and how handwashing compliance impacts hospital-acquired infections. Ambient intelligence solutions include cameras and RFID-based systems.

181. Schweickert, W. D. *et al.* Early physical and occupational therapy in mechanically ventilated, critically ill patients: a randomised controlled trial. *Lancet* **373**, 1874–1882 (2009).
182. Tipping, C. J. *et al.* The effects of active mobilisation and rehabilitation in ICU on mortality and function: a systematic review. *Intensive Care Med.* **43**, 171–183 (2017).
183. Berney, S. C., Rose, J. W., Bernhardt, J. & Denehy, L. Prospective observation of physical activity in critically ill patients who were intubated for more than 48 hours. *J. Crit. Care* **30**, 658–663 (2015).
184. Rawat, N. *et al.* Comparison of Automated Activity Recognition to Provider Observations of Patient Mobility in the ICU. *Crit. Care Med.* **47**, 1232–1234 (2019).
185. Banerjee, T. *et al.* Monitoring patients in hospital beds using unobtrusive depth sensors. in *International Conference of the IEEE Engineering in Medicine and Biology Society* vol. 2014 5904–5907 (2014).
186. Reiter, A., Ma, A., Rawat, N., Shrock, C. & Saria, S. Process Monitoring in the Intensive Care Unit: Assessing Patient Mobility Through Activity Analysis with a Non-Invasive Mobility Sensor. *Med. Image Comput. Comput. Assist. Interv.* **9900**, 482–490 (2016).
187. Pittet, D. *et al.* Effectiveness of a hospital-wide programme to improve compliance with hand hygiene. *Lancet* **356**, 1307–1312 (2000).
188. Dasgupta, S., Das, S., Chawan, N. S. & Hazra, A. Nosocomial infections in the intensive care unit: Incidence, risk factors, outcome and associated pathogens in a public tertiary teaching hospital of Eastern India. *Indian J. Crit. Care Med.* **19**, 14–20 (2015).
189. Pineles, L. L. *et al.* Accuracy of a radiofrequency identification (RFID) badge system to monitor hand hygiene behavior during routine clinical activities. *Am. J. Infect. Control* **42**, 144–147 (2014).
190. Marra, A. R., Moura, D. F., Jr, Paes, A. T., dos Santos, O. F. P. & Edmond, M. B. Measuring rates of hand hygiene adherence in the intensive care setting: a comparative study of direct observation, product usage, and electronic counting devices. *Infect. Control Hosp. Epidemiol.* **31**, 796–801 (2010).
191. Brown, J., Froese-Fretz, A., Luckey, D. & Todd, J. K. High rate of hand contamination and low rate of hand washing before infant contact in a neonatal intensive care unit. *Pediatr. Infect. Dis. J.* **15**, 908–910 (1996).
192. Nishimura, S., Kagehira, M., Kono, F., Nishimura, M. & Taenaka, N. Handwashing before entering the intensive care unit: what we learned from continuous video-camera surveillance. *Am. J. Infect. Control* **27**, 367–369 (1999).
193. Armellino, D. *et al.* Replicating changes in hand hygiene in a surgical intensive care unit with remote video auditing and feedback. *Am. J. Infect. Control* **41**, 925–927 (2013).
194. Guo, M. *et al.* Viewpoint Invariant Convolutional Networks for Identifying Risky Hand

Hygiene Scenarios. *Workshop on Machine Learning for Health* (2017).
195. Kable, A. K., Gibberd, R. W. & Spigelman, A. D. Adverse events in surgical patients in Australia. *Int. J. Qual. Health Care* **14**, 269–276 (2002).
196. Sharma, S. Objective assessment of technical skills in surgery: assessment should include decision making. *BMJ* vol. 328 403 (2004).
197. Xeroulis, G. J. *et al.* Teaching suturing and knot-tying skills to medical students: a randomized controlled study comparing computer-based video instruction and (concurrent and summary) expert feedback. *Surgery* **141**, 442–449 (2007).
198. Martin, L. *et al.* Trainee surgery in teaching hospitals: is there a cost? *Australian and New Zealand Journal of Surgery* **59**, 257–260 (1989).
199. Xu, S., Jayaraman, A. & Rogers, J. A. Skin sensors are the future of health care. *Nature* **571**, 319–321 (2019).
200. Ward, M. A. *et al.* Automated and electronically assisted hand hygiene monitoring systems: a systematic review. *Am. J. Infect. Control* **42**, 472–478 (2014).
201. van de Mortel, T. & Murgo, M. An examination of covert observation and solution audit as tools to measure the success of hand hygiene interventions. *Am. J. Infect. Control* **34**, 95–99 (2006).
202. Won, S.-P. *et al.* Handwashing program for the prevention of nosocomial infections in a neonatal intensive care unit. *Infect. Control Hosp. Epidemiol.* **25**, 742–746 (2004).
203. Gould, D. J., Drey, N. S., Moralejo, D., Grimshaw, J. & Chudleigh, J. Interventions to improve hand hygiene compliance in patient care. *J. Hosp. Infect.* **68**, 193–202 (2008).

B.2. Operating Rooms

The below references propose technological solutions for detecting and manipulating surgical instruments using computer vision algorithms. Additional references are provided regarding laparoscopic surgery, video-based workflow recognition, and surgical guidelines proposed by clinical organizations.

B.3. Other Healthcare Spaces

These references provide further reading regarding speech recognition for medical documentation and time-driven activity-based costing for medical billing and healthcare management purposes.

219. Borowitz, S. M. Computer-based speech recognition as an alternative to medical transcription. *J. Am. Med. Inform. Assoc.* **8**, 101–102 (2001).
220. Rajkomar, A. *et al.* Automatically Charting Symptoms From Patient-Physician Conversations Using Machine Learning. *JAMA Intern. Med.* **179**, 836–838 (2019).
221. Canby, J. B., 4th. Applying activity-based costing to healthcare settings. *Healthc. Financ. Manage.* **49**, 50–2, 54–6 (1995).
222. Inverso, G. *et al.* Increasing value in plagiocephaly care: a time-driven activity-based

costing pilot study. *Ann. Plast. Surg.* **74**, 672–676 (2015).
223. Laviana, A. A. *et al.* Utilizing time-driven activity-based costing to understand the short- and long-term costs of treating localized, low-risk prostate cancer. *Cancer* **122**, 447–455 (2016).
224. Erhun, F. *et al.* Time-driven activity-based costing of multivessel coronary artery bypass grafting across national boundaries to identify improvement opportunities: study protocol. *BMJ Open* **5**, e008765 (2015).
225. Campanale, C., Cinquini, L. & Tenucci, A. Time-driven activity-based costing to improve transparency and decision making in healthcare: A case study. *Qualitative Research in Accounting & Management* **11**, 165–186 (2014).
226. Zhou, L. *et al.* Analysis of Errors in Dictated Clinical Documents Assisted by Speech Recognition Software and Professional Transcriptionists. *JAMA Netw Open* **1**, e180530 (2018).
227. Porter, M. E. What Is Value in Health Care? *N. Engl. J. Med.* **363**, 2477–2481 (2010).
228. Kaplan, R. S. & Porter, M. E. How to solve the cost crisis in health care. *Harv. Bus. Rev.* **89**, (2011).

C. Daily Living Spaces

The references below provide additional statistics which underscore the aging problem and relevance of daily living spaces in the context of independent senior living, chronic disease management, and mental health.

229. Redfoot, D., Feinberg, L. & Houser, A. *The Aging of the Baby Boom and the Growing Care Gap: A Look at Future Declines in the Availability of Family Caregivers*. (2013).
230. Harris-Kojetin, L. *et al.* Long-Term Care Providers and Services Users in the United States: Data From the National Study of Long-Term Care Providers, 2013-2014. *Vital and Health Statistics* **38**, 1–105 (2016).
231. Alzheimer’s Association. 2020 Alzheimer’s Disease Facts and Figures. *Alzheimers. Dement.* **16**, 391–460 (2020).

C.1. Senior Living & Aging

Further background reading on the activities of daily living and fall detection, including relevant assessments, grading rubrics, and scales, is provided below. Systematic reviews and original research articles covering wearable devices and ambient sensors are also included.

232. Lubitz, J., Cai, L., Kramarow, E. & Lentzner, H. Health, life expectancy, and health care spending among the elderly. *N. Engl. J. Med.* **349**, 1048–1055 (2003).
233. Leenerts, M. H., Teel, C. S. & Pendleton, M. K. Building a model of self-care for health promotion in aging. *J. Nurs. Scholarsh.* **34**, 355–361 (2002).

234. Mlinac, M. E. & Feng, M. C. Assessment of Activities of Daily Living, Self-Care, and Independence. *Arch. Clin. Neuropsychol.* **31**, 506–516 (2016).
235. Lawton, M. P. & Brody, E. M. Assessment of Older People: Self-Maintaining and Instrumental Activities of Daily Living. *The Gerontologist* **9**, 179–186 (1969).
236. Shulman, L. M. *et al.* Subjective report versus objective measurement of activities of daily living in Parkinson's disease. *Mov. Disord.* **21**, 794–799 (2006).
237. Zanetti, O., Geroldi, C., Frisoni, G. B., Bianchetti, A. & Trabucchi, M. Contrasting Results Between Caregiver's Report and Direct Assessment of Activities of Daily Living in Patients Affected by Mild and Very Mild Dementia: The Contribution of the Caregiver's Personal Characteristics. *Journal of the American Geriatrics Society* **47**, 196–202 (1999).
238. de Bruin, E. D., Hartmann, A., Uebelhart, D., Murer, K. & Zijlstra, W. Wearable systems for monitoring mobility-related activities in older people: a systematic review. *Clin. Rehabil.* **22**, 878–895 (2008).
239. Mahoney, F. I. & Barthel, D. W. Functional Evaluation: The Barthel Index. *Maryland State Medical Journal* **14**, 56–61 (1965).
240. Jimison, H., Jessey, N., McKanna, J., Zitzelberger, T. & Kaye, J. Monitoring Computer Interactions to Detect Early Cognitive Impairment in Elders. in *Conference on Distributed Diagnosis and Home Healthcare* 75–78 (IEEE, 2006).
241. Fauth, E. B., Femia, E. E. & Zarit, S. H. Resistiveness to care during assistance with activities of daily living in non-institutionalized persons with dementia: associations with informal caregivers' stress and well-being. *Aging Ment. Health* **20**, 888–898 (2016).
242. Wiener, J. M., Hanley, R. J., Clark, R. & Van Nostrand, J. F. Measuring the activities of daily living: comparisons across national surveys. *J. Gerontol.* **45**, S229–37 (1990).
243. Allet, L., Knols, R. H., Shirato, K. & de Bruin, E. D. Wearable systems for monitoring mobility-related activities in chronic disease: a systematic review. *Sensors* **10**, 9026–9052 (2010).
244. Tedesco, S., Barton, J. & O'Flynn, B. A Review of Activity Trackers for Senior Citizens: Research Perspectives, Commercial Landscape and the Role of the Insurance Industry. *Sensors* **17**, (2017).
245. Bao, L. & Intille, S. S. Activity Recognition from User-Annotated Acceleration Data. in *Pervasive Computing* 1–17 (Springer, 2004).
246. Pal, S. & Abhayaratne, C. Video-based activity level recognition for assisted living using motion features. In *International Conference on Distributed Smart Cameras* 62–67 (2015).
247. Ghose, A. *et al.* UbiHeld - Ubiquitous Healthcare Monitoring System for Elderly and Chronic Patients. In *Workshop on Human Factors and Activity Recognition in Healthcare, Wellness and Assisted Living* 1255–1264 (ACM, 2013).
248. Xiang, Y. *et al.* Remote safety monitoring for elderly persons based on omni-vision

analysis. *PLOS One* **10**, e0124068 (2015).
249. Parajuli, M., Tran, D., Ma, W. & Sharma, D. Senior health monitoring using Kinect. In *International Conference on Communications and Electronics* 309–312 (IEEE, 2012).
250. Barnan Das, Narayanan C. Krishnan, Diane J. Cook. Automated Activity Interventions to Assist with Activities of Daily Living. In *Ambient Intelligence and Smart Environments* vol. 12 137–158 (IOS Press, 2012).
251. Noury, N. *et al.* Monitoring behavior in home using a smart fall sensor and position sensors. In *Conference on Microtechnologies in Medicine and Biology* 607–610 (IEEE, 2000).
252. Lindemann, U., Hock, A., Stuber, M., Keck, W. & Becker, C. Evaluation of a fall detector based on accelerometers: a pilot study. *Med. Biol. Eng. Comput.* **43**, 548–551 (2005).
253. Hwang, J. Y., Kang, J. M., Jang, Y. W. & Kim, H. Development of novel algorithm and real-time monitoring ambulatory system using Bluetooth module for fall detection in the elderly. *Conf. Proc. IEEE Eng. Med. Biol. Soc.* **2004**, 2204–2207 (2004).
254. Xiaodan Zhuang, Huang, J., Potamianos, G. & Hasegawa-Johnson, M. Acoustic fall detection using Gaussian mixture models and GMM supervectors. In *International Conference on Acoustics, Speech and Signal Processing* 69–72 (IEEE, 2009).
255. Wang, S., Chen, L., Zhou, Z., Sun, X. & Dong, J. Human fall detection in surveillance video based on PCANet. *Multimed. Tools Appl.* **75**, 11603–11613 (2016).
256. Lu, N., Wu, Y., Feng, L. & Song, J. Deep Learning for Fall Detection: Three-Dimensional CNN Combined With LSTM on Video Kinematic Data. *IEEE J Biomed Health Inform* **23**, 314–323 (2019).
257. Núñez-Marcos, A., Azkune, G. & Arganda-Carreras, I. Vision-based fall detection with convolutional neural networks. *Wireless Communications and Mobile Computing* **2017**, (2017).
258. Zhang, Z., Conly, C. & Athitsos, V. A survey on vision-based fall detection. In *International Conference on Pervasive Technologies Related to Assistive Environments* 1–7 (ACM, 2015).
259. Jokanovic, B., Amin, M. & Ahmad, F. Radar fall motion detection using deep learning. In *IEEE Radar Conference* 1–6 (2016).
260. Jokanović, B. & Amin, M. Fall Detection Using Deep Learning in Range-Doppler Radars. *IEEE Trans. Aerosp. Electron. Syst.* **54**, 180–189 (2018).
261. Gasparrini, S., Cippitelli, E., Spinsante, S. & Gambi, E. A Depth-Based Fall Detection System Using a Kinect Sensor. *Sensors* **14**, 2756–2775 (2014).
262. Mastorakis, G. & Makris, D. Fall detection system using Kinect's infrared sensor. *Journal of Real-Time Image Processing* **9**, 635–646 (2014).
263. Bevilacqua, V. *et al.* Fall detection in indoor environment with kinect sensor. In *International Symposium on Innovations in Intelligent Systems and Applications* 319–324 (IEEE, 2014).

264. Anh Tuan Nghiem, Auvinet, E. & Meunier, J. Head detection using Kinect camera and its application to fall detection. In *International Conference on Information Science, Signal Processing and their Applications* 164–169 (IEEE, 2012).
265. Chan, J., Rea, T., Gollakota, S. & Sunshine, J. E. Contactless cardiac arrest detection using smart devices. *NPJ Digit Med* **2**, 52 (2019).

C.2. Chronic Disease Management

The references below discuss how wearable devices and ambient sensors are used for physical rehabilitation and gait analysis in the context of several chronic diseases, including chronic obstructive pulmonary disease and Parkinson's disease.

266. Zago, M., Sforza, C., Bonardi, D. R., Guffanti, E. E. & Galli, M. Gait analysis in patients with chronic obstructive pulmonary disease: a systematic review. *Gait Posture* **61**, 408–415 (2018).
267. Schink, K. *et al.* Assessment of gait parameters and physical function in patients with advanced cancer participating in a 12-week exercise and nutrition programme: A controlled clinical trial. *Eur. J. Cancer Care* **29**, e13199 (2020).
268. Gordt, K., Gerhardy, T., Najafi, B. & Schwenk, M. Effects of wearable sensor-based balance and gait training on balance, gait, and functional performance in healthy and patient populations: a systematic review and meta-analysis of randomized controlled trials. *Gerontology* **64**, 74–89 (2018).
269. Rabinovich, R. A. *et al.* Validity of physical activity monitors during daily life in patients with COPD. *Eur. Respir. J.* **42**, 1205–1215 (2013).
270. Pistacchi, M. *et al.* Gait analysis and clinical correlations in early Parkinson's disease. *Funct. Neurol.* **32**, 28–34 (2017).
271. American Thoracic Society. ATS statement: guidelines for the six-minute walk test. *Am. J. Respir. Crit. Care Med.* **166**, 111–117 (2002).
272. Zhang, B., Jiang, S., Wei, D., Marschollek, M. & Zhang, W. State of the Art in Gait Analysis Using Wearable Sensors for Healthcare Applications. In *International Conference on Computer and Information Science* 213–218 (IEEE, 2012).
273. Iso, T. & Yamazaki, K. Gait analyzer based on a cell phone with a single three-axis accelerometer. In *Conference on Human-Computer Interaction with Mobile Devices and Services* 141–144 (ACM, 2006).
274. Shull, P. B., Jirattigalachote, W., Hunt, M. A., Cutkosky, M. R. & Delp, S. L. Quantified self and human movement: a review on the clinical impact of wearable sensing and feedback for gait analysis and intervention. *Gait Posture* **40**, 11–19 (2014).
275. Gu, X., Deligianni, F., Lo, B., Chen, W. & Yang, G. Z. Markerless gait analysis based on a single RGB camera. In *International Conference on Wearable and Implantable Body Sensor Networks* 42–45 (IEEE, 2018).
276. Nieto-Hidalgo, M., Ferrández-Pastor, F. J., Valdivieso-Sarabia, R. J., Mora-Pascual, J.

& García-Chamizo, J. M. A vision based proposal for classification of normal and abnormal gait using RGB camera. *J. Biomed. Inform.* **63**, 82–89 (2016).

277. Müller, B., Ilg, W., Giese, M. A. & Ludolph, N. Validation of enhanced kinect sensor based motion capturing for gait assessment. *PLOS One* **12**, e0175813 (2017).
278. Atanasov, M. & Kampel, M. Automated Determination of Gait Parameters Using Depth Based Person Tracking. In *International Conference on Embedded and Ubiquitous Computing* 96–102 (IEEE, 2018).
279. Xue, D. *et al.* Vision-Based Gait Analysis for Senior Care. In *Workshop on Machine Learning for Health* (2018).
280. Rocha, A. P. *et al.* Parkinson's disease assessment based on gait analysis using an innovative RGB-D camera system. *Conf. Proc. IEEE Eng. Med. Biol. Soc.* **2014**, 3126–3129 (2014).
281. Chattopadhyay, P., Sural, S. & Mukherjee, J. Frontal Gait Recognition From Incomplete Sequences Using RGB-D Camera. *Trans. Inf. Forensics Secur.* **9**, 1843–1856 (2014).
282. Mousavi Hondori, H. & Khademi, M. A Review on Technical and Clinical Impact of Microsoft Kinect on Physical Therapy and Rehabilitation. *J. Med. Eng. Technol.* **2014**, 846514 (2014).
283. Wang, C. *et al.* Estimation of Temporal Gait Parameters Using a Wearable Microphone-Sensor-Based System. *Sensors* **16**, (2016).
284. Vamsikrishna, K. M., Dogra, D. P. & Desarkar, M. S. Computer-Vision-Assisted Palm Rehabilitation With Supervised Learning. *IEEE Trans. Biomed. Eng.* **63**, 991–1001 (2016).

C.3. Mental Health

Below, the references provide additional sources regarding population-level mental health statistics and include citations to clinically-validated assessment tools and guidelines. Several technology-based approaches to diagnostic screening are also provided below.

285. Kroenke, K. *et al.* The PHQ-8 as a measure of current depression in the general population. *Journal of Affective Disorders* **114**, 163–173 (2009).
286. Spitzer, R. L., Kroenke, K., Williams, J. B. W. & Löwe, B. A brief measure for assessing generalized anxiety disorder: the GAD-7. *Arch. Intern. Med.* **166**, 1092–1097 (2006).
287. Substance Abuse and Mental Health Services Administration, U.S. Department of Health and Human Services. *Key substance use and mental health indicators in the United States: Results from the 2018 National Survey on Drug Use and Health*. (2019).
288. American Psychiatric Association. *Diagnostic and Statistical Manual of Mental Disorders (DSM-5)*. (American Psychiatric Pub, 2013).
289. Kim, H., Bracha, Y. & Tipnis, A. Automated depression screening in disadvantaged

pregnant women in an urban obstetric clinic. *Arch. Womens. Ment. Health* **10**, 163–169 (2007).
290. Haque, A., Guo, M., Miner, A. S. & Fei-Fei, L. Measuring Depression Symptom Severity from Spoken Language and 3D Facial Expressions. In *Workshop on Machine Learning for Health* (2018).
291. Low, D. M., Bentley, K. H. & Ghosh, S. S. Automated assessment of psychiatric disorders using speech: A systematic review. *Laryngoscope Investig Otolaryngol* **5**, 96–116 (2020).
292. Muñoz, R. F., McQuaid, J. R., González, G. M., Dimas, J. & Rosales, V. A. Depression screening in a women's clinic: Using automated Spanish- and English-language voice recognition. *Journal of Consulting and Clinical Psychology* **67**, 502–510 (1999).
293. Al Hanai, T., Ghassemi, M. M. & Glass, J. R. Detecting Depression with Audio/Text Sequence Modeling of Interviews. In *Interspeech* 1716–1720 (ISCA, 2018).
294. Adams, P. *et al.* Towards personal stress informatics: comparing minimally invasive techniques for measuring daily stress in the wild. In *International Conference on Pervasive Computing Technologies for Healthcare* 72–79 (2014).
295. Imel, Z. E., Steyvers, M. & Atkins, D. C. Computational psychotherapy research: scaling up the evaluation of patient-provider interactions. *Psychotherapy* **52**, 19–30 (2015).
296. Xiao, B. *et al.* Behavioral Coding of Therapist Language in Addiction Counseling Using Recurrent Neural Networks. In *Interspeech* 908–912 (ISCA, 2016).

D. Technical Challenges and Opportunities

This section provides additional references regarding computer vision, speech recognition, natural language processing, and machine learning, both inside and outside of healthcare.

D.1. Behavior Recognition in Complex Scenes

These references provide further reading on topics related to human behavior recognition in complex scenes. This includes technical subjects such as human pose estimation, audio denoising, activity detection, scene graph parsing and generation.

297. Takala, V. & Pietikainen, M. Multi-Object Tracking Using Color, Texture and Motion. In *Conference on Computer Vision and Pattern Recognition* 1–7 (IEEE, 2007).
298. He, K., Zhang, X., Ren, S. & Sun, J. Deep residual learning for image recognition. In *Conference on Computer Vision and Pattern Recognition* 770–778 (IEEE, 2016).
299. Chen, Z., Luo, Y. & Mesgarani, N. Deep attractor network for single-microphone speaker separation. In *International Conference on Acoustics, Speech and Signal Processing* 246–250 (IEEE, 2017).
300. Zhou, H., Liu, Z., Xu, X., Luo, P. & Wang, X. Vision-Infused Deep Audio Inpainting.

In *International Conference on Computer Vision* 283–292 (IEEE/CVF, 2019).
301. Yeh, R. A. *et al.* Semantic image inpainting with deep generative models. In *Conference on Computer Vision and Pattern Recognition* 5485–5493 (IEEE, 2017).
302. Papandreou, G. *et al.* Towards accurate multi-person pose estimation in the wild. In *Conference on Computer Vision and Pattern Recognition* 4903–4911 (IEEE, 2017).
303. Insafutdinov, E., Pishchulin, L., Andres, B., Andriluka, M. & Schiele, B. DeeperCut: A Deeper, Stronger, and Faster Multi-person Pose Estimation Model. In *European Conference on Computer Vision* 34–50 (Springer, 2016).
304. Newell, A., Yang, K. & Deng, J. Stacked Hourglass Networks for Human Pose Estimation. In *European Conference on Computer Vision* 483–499 (Springer, 2016).
305. Toshev, A. & Szegedy, C. Deeppose: Human pose estimation via deep neural networks. In *Conference on Computer Vision and Pattern Recognition* 1653–1660 (IEEE, 2014).
306. Cao, Z., Simon, T., Wei, S.-E. & Sheikh, Y. Realtime multi-person 2d pose estimation using part affinity fields. In *Conference on Computer Vision and Pattern Recognition* 7291–7299 (IEEE, 2017).
307. Martinez, J., Hossain, R., Romero, J. & Little, J. J. A simple yet effective baseline for 3d human pose estimation. In *International Conference on Computer Vision* 2640–2649 (IEEE, 2017).
308. Haque, A. *et al.* Towards Viewpoint Invariant 3D Human Pose Estimation. In *European Conference on Computer Vision* 160–177 (Springer, 2016).
309. Mehta, D., Sridhar, S., Sotnychenko, O. & Rhodin, H. VNect: Real-time 3D Human Pose Estimation with a Single RGB Camera. *ACM Transactions on Graphics* **36**, 1–14 (2017).
310. Nath, T. *et al.* Using DeepLabCut for 3D markerless pose estimation across species and behaviors. *Nat. Protoc.* **14**, 2152–2176 (2019).
311. Yao, B. & Fei-Fei, L. Modeling mutual context of object and human pose in human-object interaction activities. In *Conference on Computer Vision and Pattern Recognition* 17–24 (IEEE, 2010).
312. Ryoo, M. S. & Aggarwal, J. K. Hierarchical Recognition of Human Activities Interacting with Objects. In *Conference on Computer Vision and Pattern Recognition* 1–8 (IEEE, 2007).
313. Gkioxari, G., Girshick, R., Dollár, P. & He, K. Detecting and recognizing human-object interactions. In *Conference on Computer Vision and Pattern Recognition* 8359–8367 (IEEE/CVF, 2018).
314. Escorcia, V. & Niebles, J. Spatio-temporal human-object interactions for action recognition in videos. In *International Conference on Computer Vision Workshops* 508–514 (2013).
315. Lu, C., Krishna, R., Bernstein, M. & Fei-Fei, L. Visual Relationship Detection with Language Priors. In *European Conference on Computer Vision* 852–869 (Springer, 2016).

316. Yu, R., Li, A., Morariu, V. I. & Davis, L. S. Visual relationship detection with internal and external linguistic knowledge distillation. In *International Conference on Computer Vision* 1974–1982 (2017).
317. Yao, T., Pan, Y., Li, Y. & Mei, T. Exploring visual relationship for image captioning. In *European Conference on Computer Vision* 684–699 (Springer, 2018).
318. Dai, B., Zhang, Y. & Lin, D. Detecting visual relationships with deep relational networks. In *Conference on Computer Vision and Pattern Recognition* 3076–3086 (IEEE, 2017).
319. Ji, J., Krishna, R., Fei-Fei, L. & Niebles, J. C. Action Genome: Actions as Composition of Spatio-temporal Scene Graphs. In *Conference on Computer Vision and Pattern Recognition* (IEEE/CVF, 2020).
320. Xu, D., Zhu, Y., Choy, C. B. & Fei-Fei, L. Scene graph generation by iterative message passing. In *Conference on Computer Vision and Pattern Recognition* 5410–5419 (IEEE, 2017).
321. Johnson, J., Gupta, A. & Fei-Fei, L. Image generation from scene graphs. In *Conference on Computer Vision and Pattern Recognition* 1219–1228 (IEEE/CVF, 2018).
322. Zellers, R., Yatskar, M., Thomson, S. & Choi, Y. Neural motifs: Scene graph parsing with global context. In *Conference on Computer Vision and Pattern Recognition* 5831–5840 (IEEE, 2018).
323. Koppula, H. & Saxena, A. Learning Spatio-Temporal Structure from RGB-D Videos for Human Activity Detection and Anticipation. In *International Conference on Machine Learning* 792–800 (PMLR, 2013).
324. Zhang, J., Shih, K., Tao, A., Catanzaro, B. & Elgammal, A. An Interpretable Model for Scene Graph Generation. In *Workshop on Visually Grounded Interaction and Language* (2018).

D.2. Learning From Big Data and Rare Events

The references below cover technical topics related to theoretical machine learning algorithms, data and model representations, hardware optimizations, and statistical model calibration.

325. Schaeffer, C., Booton, L., Halleck, J., Studeny, J. & Coustasse, A. Big Data Management in US Hospitals: Benefits and Barriers. *Health Care Manag.* **36**, 87–95 (2017).
326. Mukkamala, M. C. & Hein, M. Variants of RMSProp and Adagrad with Logarithmic Regret Bounds. In *International Conference on Machine Learning* 2545–2553 (PMLR, 2017).
327. Ward, R., Wu, X. & Bottou, L. AdaGrad Stepsizes: Sharp Convergence Over Nonconvex Landscapes. In *International Conference on Machine Learning* 6677–6686 (PMLR, 2019).

328. Kingma, D. P. & Ba, J. Adam: A Method for Stochastic Optimization. In *International Conference on Learning Representations* (2015).
329. Jia, X. *et al.* Highly Scalable Deep Learning Training System with Mixed-Precision: Training ImageNet in Four Minutes. *arXiv [cs.LG]* (2018).
330. Hannun, A., Lee, A., Xu, Q. & Collobert, R. Sequence-to-Sequence Speech Recognition with Time-Depth Separable Convolutions. In *Interspeech* 3785–3789 (ISCA, 2019).
331. Wang, L., Xiong, Y., Wang, Z. & Qiao, Y. Towards Good Practices for Very Deep Two-Stream ConvNets. *arXiv [cs.CV]* (2015).
332. Zhang, B., Wang, L., Wang, Z., Qiao, Y. & Wang, H. Real-time action recognition with enhanced motion vector CNNs. In *Conference on Computer Vision and Pattern Recognition* 2718–2726 (IEEE, 2016).
333. Ng, J. Y., Choi, J., Neumann, J. & Davis, L. S. ActionFlowNet: Learning Motion Representation for Action Recognition. In *Winter Conference on Applications of Computer Vision* 1616–1624 (IEEE, 2018).
334. Iandola, F. N. *et al.* SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and< 0.5 MB model size. *arXiv preprint arXiv:1602. 07360* (2016).
335. He, Y. *et al.* Amc: Automl for model compression and acceleration on mobile devices. In *European Conference on Computer Vision* 784–800 (Springer, 2018).
336. Zhou, A., Yao, A., Guo, Y., Xu, L. & Chen, Y. Incremental Network Quantization: Towards Lossless CNNs with Low-Precision Weights. In *International Conference on Learning Representations* (2017).
337. Deng, L., Li, G., Han, S., Shi, L. & Xie, Y. Model Compression and Hardware Acceleration for Neural Networks: A Comprehensive Survey. *Proc. IEEE* **108**, 485–532 (2020).
338. Buch, S., Escorcia, V., Shen, C., Ghanem, B. & Carlos Niebles, J. Sst: Single-stream temporal action proposals. In *Conference on Computer Vision and Pattern Recognition* 2911–2920 (IEEE, 2017).
339. Escorcia, V., Caba Heilbron, F., Niebles, J. C. & Ghanem, B. DAPs: Deep Action Proposals for Action Understanding. In *European Conference on Computer Vision* 768–784 (Springer, 2016).
340. Osborne, C. Statistical Calibration: A Review. *Int. Stat. Rev.* **59**, 309–336 (1991).
341. Pierson, E., Corbett-Davies, S. & Goel, S. Fast Threshold Tests for Detecting Discrimination. *arXiv [stat.ML]* (2017).
342. Corbett-Davies, S. & Goel, S. The Measure and Mismeasure of Fairness: A Critical Review of Fair Machine Learning. *arXiv [cs.CY]* (2018).
343. Simoiu, C., Corbett-Davies, S. & Goel, S. The problem of infra-marginality in outcome tests for discrimination. *Ann. Appl. Stat.* **11**, 1193–1216 (2017).
344. Bengio, Y. Deep learning of representations for unsupervised and transfer learning. In *Workshop on Unsupervised and Transfer Learning* 17–36 (PMLR, 2012).

345. Long, M., Zhu, H., Wang, J. & Jordan, M. I. Unsupervised Domain Adaptation with Residual Transfer Networks. *Advances in Neural Information Processing Systems* **29**, 136–144 (2016).
346. Donahue, J. *et al.* DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition. In *International Conference on Machine Learning* 647–655 (2014).

E. Social and Ethical Considerations

To better illustrate the interdisciplinary implications of ambient intelligence, papers from multiple subject areas, such as philosophy, computer science, medicine, and public policy, are included below.

347. Zhou, J. & Chen, F. *Human and Machine Learning: Visible, Explainable, Trustworthy and Transparent*. (Springer, 2018).
348. Winfield, A. F. T. & Jirotka, M. Ethical governance is essential to building trust in robotics and artificial intelligence systems. *Philos. Trans. A Math. Phys. Eng. Sci.* **376**, 20180085 (2018).
349. Rigby, M. J. Ethical Dimensions of Using Artificial Intelligence in Health Care. *AMA Journal of Ethics* **21**, 121–124 (2019).

E.1. Privacy

The references below include commentaries by the healthcare community on the topic of privacy, as well as highly-technical algorithmic and mathematical approaches to computational privacy.

350. Bartoletti, I. AI in Healthcare: Ethical and Privacy Challenges. In *Artificial Intelligence in Medicine* 7–10 (Springer, 2019).
351. Ginart, A., Guan, M., Valiant, G. & Zou, J. Y. Making AI Forget You: Data Deletion in Machine Learning. *Advances in Neural Information Processing Systems* **32**, 3518–3531 (2019).
352. Kostkova, P. *et al.* Who Owns the Data? Open Data for Healthcare. *Front Public Health* **4**, 7 (2016).
353. Ryoo, M. S., Rothrock, B., Fleming, C. & Yang, H. J. Privacy-preserving human activity recognition from extreme low resolution. In *AAAI Conference on Artificial Intelligence* (2017).
354. Konečný, J. *et al.* Federated Learning: Strategies for Improving Communication Efficiency. *arXiv [cs.LG]* (2016).
355. Liu, Z., Li, T., Smith, V. & Sekar, V. Enhancing the Privacy of Federated Learning with Sketching. *arXiv [cs.LG]* (2019).
356. Sandbrook, C., Luque-Lora, R. & Adams, W. M. Human bycatch: conservation

surveillance and the social implications of camera traps. *Conservation and Society* **16**, 493–504 (2018).

357. He, K., Gkioxari, G., Dollár, P. & Girshick, R. Mask R-CNN. In *International Conference on Computer Vision* 2980–2988 (IEEE, 2017).
358. Wieland, S. C., Cassa, C. A., Mandl, K. D. & Berger, B. Revealing the spatial distribution of a disease while preserving privacy. *Proc. Natl. Acad. Sci. U. S. A.* **105**, 17608–17613 (2008).
359. Wang, J. *et al.* A Scalable and Privacy-Aware IoT Service for Live Video Analytics. In *Multimedia Systems Conference* 38–49 (ACM, 2017).
360. Chen, J., Wu, J., Konrad, J. & Ishwar, P. Semi-Coupled Two-Stream Fusion ConvNets for Action Recognition at Extremely Low Resolutions. In *Winter Conference on Applications of Computer Vision* 139–147 (IEEE, 2017).
361. Papernot, N. *et al.* Scalable Private Learning with PATE. In *International Conference on Learning Representations* (2018).
362. Mohammadi, S. H. & Kain, A. An overview of voice conversion systems. *Speech Commun.* **88**, 65–82 (2017).
363. Dankar, F. & Emam, K. Practicing differential privacy in health care: A review. *Data Priv.* (2013).
364. Xu, C. *et al.* GANobfuscator: Mitigating Information Leakage Under GAN via Differential Privacy. *IEEE Trans. Inf. Forensics Secur.* **14**, 2358–2371 (2019).
365. Acar, A., Aksu, H., Uluagac, A. S. & Conti, M. A Survey on Homomorphic Encryption Schemes: Theory and Implementation. *ACM Computing Surveys* **51**, 79 (2018).
366. Papernot, N., Abadi, M., Erlingsson, Ú., Goodfellow, I. & Talwar, K. Semi-supervised Knowledge Transfer for Deep Learning from Private Training Data. In *International Conference on Learning Representations* (2017).
367. Chou, E. *et al.* Faster CryptoNets: Leveraging Sparsity for Real-World Encrypted Inference. *arXiv [cs.CR]* (2018).
368. Juvekar, C., Vaikuntanathan, V. & Chandrakasan, A. GAZELLE: A low latency framework for secure neural network inference. In *USENIX Security Symposium* 1651–1669 (2018).
369. Wagh, S., Gupta, D. & Chandran, N. SecureNN: Efficient and Private Neural Network Training. In *Privacy Enhancing Technologies Symposium* (2019).
370. Chou, E. *et al.* Privacy-Preserving Action Recognition for Smart Hospitals using Low-Resolution Depth Images. In *Workshop on Machine Learning for Health* (2018).
371. Chung, H., Iorga, M., Voas, J. & Lee, S. Alexa, Can I Trust You? *Computer* **50**, 100–104 (2017).
372. Shi, W., Cao, J., Zhang, Q., Li, Y. & Xu, L. Edge Computing: Vision and Challenges. *IEEE Internet of Things Journal* **3**, 637–646 (2016).
373. Epstein, K. Police think Amazon's Alexa may have information on a fatal stabbing case. *The Washington Post* (2019).

374. Shuman, D. W. & Weiner, M. S. Privilege Study: An Empirical Examination of the Psychotherapist--Patient Privilege, The. *NCL Rev.* **60**, 893 (1981).

E.2. Fairness

Further reading on algorithmic fairness and its societal implications are provided below. This includes case studies inside and outside of healthcare. References to additional computational and statistical methods are also provided.

375. Kallus, N. & Zhou, A. The Fairness of Risk Scores Beyond Classification: Bipartite Ranking and the xAUC Metric. *Adv. Neural Inf. Process. Syst.* **32**, (2019).
376. Kallus, N. & Zhou, A. Residual Unfairness in Fair Machine Learning from Prejudiced Data. In *International Conference on Machine Learning* 2439–2448 (PMLR, 2018).
377. Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K. & Galstyan, A. A Survey on Bias and Fairness in Machine Learning. *arXiv [cs.LG]* (2019).
378. Caliskan, A., Bryson, J. J. & Narayanan, A. Semantics derived automatically from language corpora contain human-like biases. *Science* **356**, 183–186 (2017).
379. Dressel, J. & Farid, H. The accuracy, fairness, and limits of predicting recidivism. *Sci Adv* **4**, eaao5580 (2018).
380. Rahwan, I. *et al.* Machine behaviour. *Nature* **568**, 477–486 (2019).
381. Gianfrancesco, M. A., Tamang, S., Yazdany, J. & Schmajuk, G. Potential Biases in Machine Learning Algorithms Using Electronic Health Record Data. *JAMA Intern. Med.* **178**, 1544–1547 (2018).
382. Parikh, R. B., Teeple, S. & Navathe, A. S. Addressing Bias in Artificial Intelligence in Health Care. *JAMA* **322**, 2377–2378 (2019).
383. Ferryman, K. & Pitcan, M. Fairness in precision medicine. *Data & Society* (2018).
384. Aizer, A. A. *et al.* Lack of reduction in racial disparities in cancer-specific mortality over a 20-year period. *Cancer* **120**, 1532–1539 (2014).
385. Need, A. C. & Goldstein, D. B. Next generation disparities in human genomics: concerns and remedies. *Trends Genet.* **25**, 489–494 (2009).
386. Cabitza, F., Rasoini, R. & Gensini, G. F. Unintended Consequences of Machine Learning in Medicine. *JAMA* **318**, 517–518 (2017).
387. Van der Lem, R., Van der Wee, N. J. A., Van Veen, T. & Zitman, F. G. The generalizability of antidepressant efficacy trials to routine psychiatric out-patient practice. *Psychol. Med.* **41**, 1353–1363 (2011).
388. Wisniewski, S. R. *et al.* Can phase III trial results of antidepressant medications be generalized to clinical practice? A STAR* D report. *Am. J. Psychiatry* **166**, 599–607 (2009).
389. Emam, K. E., Jonker, E., Moher, E. & Arbuckle, L. A Review of Evidence on Consent Bias in Research. *Am. J. Bioeth.* **13**, 42–44 (2013).
390. Kho, M. E., Duffett, M., Willison, D. J., Cook, D. J. & Brouwers, M. C. Written

informed consent and selection bias in observational studies using medical records: systematic review. *BMJ* **338**, b866 (2009).
391. Chouldechova, A. Fair Prediction with Disparate Impact: A Study of Bias in Recidivism Prediction Instruments. *Big Data* **5**, 153–163 (2017).
392. Hardt, M., Price, E. & Srebro, N. Equality of opportunity in supervised learning. *Advances in Neural Information Processing Systems* **29**, 3315–3323 (2016).
393. Merry, B. *et al.* Ethnic Group Differences in the Outcomes of Multidisciplinary Pain Treatment. *J. Musculoskelet. Pain* **19**, 24–30 (2011).
394. Matthews, H. W. Racial, ethnic and gender differences in response to medicines. *Drug Metabol. Drug Interact.* **12**, 77–91 (1995).

E.3. Transparency

Additional reading regarding the transparency and trustworthiness of ambient intelligence systems is provided below. This includes commentaries by the healthcare community and proposed solutions to improve model transparency.

395. Price, W. N., 2nd & Cohen, I. G. Privacy in the age of medical big data. *Nat. Med.* **25**, 37–43 (2019).
396. Ribeiro, M. T., Singh, S. & Guestrin, C. ‘Why Should I Trust You?’: Explaining the Predictions of Any Classifier. *International Conference on Knowledge Discovery and Data Mining* (2016).
397. Mittelstadt, B., Russell, C. & Wachter, S. Explaining Explanations in AI. In *Conference on Fairness, Accountability, and Transparency* 279–288 (ACM, 2019).
398. Maddox, T. M., Rumsfeld, J. S. & Payne, P. R. O. Questions for Artificial Intelligence in Health Care. *JAMA* **321**, 31–32 (2019).
399. Chen, J. H. & Asch, S. M. Machine Learning and Prediction in Medicine — Beyond the Peak of Inflated Expectations. *New England Journal of Medicine* **376**, 2507–2509 (2017).
400. Collins, G. S. & Moons, K. G. M. Reporting of artificial intelligence prediction models. *Lancet* **393**, 1577–1579 (2019).
401. Simonyan, K., Vedaldi, A. & Zisserman, A. Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps. In *International Conference on Learning Representations* (2014).
402. Rudin, C. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence* **1**, 206–215 (2019).
403. Gebru, T. *et al.* Datasheets for Datasets. *arXiv [cs.DB]* (2018).

E.4. Research Ethics

Further discussions regarding informed consent, public health, and beneficence are referenced below.

404. Pimple, K. D. Six domains of research ethics. A heuristic framework for the responsible conduct of research. *Sci. Eng. Ethics* **8**, 191–205 (2002).
405. Bharucha, A. J. *et al*. Ethical considerations in the conduct of electronic surveillance research. *J. Law Med. Ethics* **34**, 611–9, 482 (2006).
406. Marx, G. T. Ethics for the New Surveillance. *The Information Society* **14**, 171–185 (1998).
407. Schiff, D. & Borenstein, J. How Should Clinicians Communicate With Patients About the Roles of Artificially Intelligent Team Members? *AMA J Ethics* **21**, 138–145 (2019).
408. Mandava, A., Pace, C., Campbell, B., Emanuel, E. & Grady, C. The quality of informed consent: mapping the landscape. A review of empirical data from developing and developed countries. *J. Med. Ethics* **38**, 356–365 (2012).
409. Mann, S. P., Savulescu, J. & Sahakian, B. J. Facilitating the ethical use of health data for the benefit of society: electronic health records, consent and the duty of easy rescue. *Philosophical Transactions of the Royal Society A* **374**, 20160130 (2016).
410. McKinney, P. A. *et al.* A feasibility study of signed consent for the collection of patient identifiable information for a national paediatric clinical audit database. *BMJ* **330**, 877–879 (2005).
411. Fairchild, A. L. & Bayer, R. Public health. Ethics and the conduct of public health surveillance. *Science* **303**, 631–632 (2004).