

Graph Neural Network-Based Modeling of Multisensor Physiological Interactions During Physical Activity

Dev Gokhale

Department of Computer Science and Engineering, University of Nevada, Reno, Reno, NV, USA.

dev.gokhale472@unr.edu

Giorgio C. Bergman

Department of Electrical Engineering and Computer Science, University of Missouri, Columbia, MO, USA.

giorgiobergman@missouri.edu

Abstract

Continuous monitoring of physiological dynamics during physical activity has become central to precision health, athletic performance, and remote rehabilitation. However, conventional multisensor fusion models often treat sensor channels as independent streams or grid-like inputs, thereby ignoring the relational and time-varying interactions among cardiac, respiratory, electrodermal, and motion-related modalities. Graph neural networks provide a principled framework for representing these multisensor physiological interactions as graph-structured data, enabling learned relational inference under motion artifacts and nonstationary conditions. This paper develops a system-level perspective on graph neural network-based modeling of multisensor physiological interactions during physical activity. It examines architectural arrangements spanning wearable acquisition, edge preprocessing, graph construction, inference, and closed-loop feedback. The discussion foregrounds structural trade-offs among centralized and distributed processing, model expressiveness and interpretability, energy efficiency, communication overhead, and resilience to missing or degraded sensor data. Attention is also given to governance, fairness, privacy, standardization, and policy implications in deployments across heterogeneous populations and regulatory contexts. Rather than focusing on specific equations or training procedures, the paper articulates how system design decisions shape the viability and trustworthiness of graph-based physiological monitoring. Case illustrations from wearable activity recognition, remote patient monitoring, and ambient assisted living are used to clarify deployment considerations. The paper concludes with forward-looking perspectives on sustainable, accountable, and adaptive graph-based multisensor infrastructures.

Keywords

graph neural networks, multisensor physiological interactions, physical activity monitoring, wearable systems, edge intelligence, health data governance.

1. Introduction

The expansion of Internet of Things sensing infrastructures has enabled continuous acquisition of physiological and kinematic data during physical activity, moving monitoring beyond controlled laboratories into daily environments [1]. Wearable systems now integrate

accelerometers, gyroscopes, photoplethysmography, electrocardiography, electrodermal activity, skin temperature, and respiratory inductance sensors, producing heterogeneous streams with distinct sampling rates, noise profiles, and failure modes. Deep learning models for wearable activity recognition have demonstrated considerable success by learning hierarchical temporal features from multimodal channels [2]. However, most of these architectures implicitly treat sensor channels as independent or weakly coupled sources. In reality, physical activity induces coordinated physiological responses: heart rate and respiration are coupled through autonomic control, electrodermal activity responds to sympathetic arousal, and motion artifacts propagate across optical and electrical sensors in correlated ways. Ignoring such interactions limits robustness and reduces the interpretive value of the model in clinical and sports settings.

Graph neural networks offer an alternative representational approach in which sensors and physiological subsystems are modeled as nodes and their functional dependencies as edges [3]. Instead of forcing heterogeneous channels into a fixed grid, graph-based learning preserves relational structure and allows information to propagate along anatomically or statistically meaningful pathways. Attention mechanisms further permit the model to assign dynamic importance to different physiological interactions as activity intensity and emotional state change [4]. Graph signal processing provides the theoretical foundation for analyzing signals defined on irregular domains, making it possible to characterize spectral properties of physiological interaction graphs [5]. Geometric deep learning generalizes this perspective by treating graph-structured data as a fundamental class beyond Euclidean inputs, with implications for relational modeling in complex biological systems [6]. These developments support a shift from channel-centric fusion to interaction-centric fusion, which is particularly relevant when sensor availability is variable and motion artifacts disturb individual modalities.

Yet deploying such models outside research prototypes poses broad system-level challenges that are not reducible to model architecture. Data governance, patient privacy, algorithmic fairness, and infrastructure resilience become as important as predictive accuracy. Federated learning has been proposed as a way to train health-related models across distributed devices without centralizing raw physiological data [7]. Responsible machine learning frameworks emphasize the need to anticipate deployment failures, monitor performance across shifting populations, and define clinical accountability [8]. Fairness scholarship further demonstrates that models trained on biased or unrepresentative sensor data can produce differential performance across demographic and clinical subgroups [9]. These socio-technical considerations are central to graph neural network-based physiological monitoring because graph construction choices, edge weighting, and learned attention mechanisms can encode population-specific assumptions that are not immediately visible to system operators.

2. Background and Related Work

Multisensor physiological monitoring has historically relied on feature engineering and domain-specific heuristic rules, such as thresholds for heart rate zones or motion intensity counts. These approaches provide transparency but often fail when activity patterns become unstructured or when sensor placement changes. The emergence of deep multimodal learning allowed hierarchical representations to be learned directly from raw sensor streams, reducing manual feature design [2]. However, temporal deep models often concatenate channels or use shared convolutional kernels, which can obscure the fact that physiological signals have distinct physical origins and interaction dynamics. The need for relational modeling has motivated researchers to explore structured representations where domain knowledge can

guide connectivity while learning refines interaction strength [3]. In this context, graph attention mechanisms are valuable because they allow the model to learn context-dependent weighting of neighboring physiological nodes without requiring fixed adjacency matrices [4].

Graph signal processing contributes a conceptual vocabulary for evaluating how information is distributed across a physiological graph. Smoothness, spectral concentration, and localization on graphs provide useful diagnostics for understanding whether learned sensor relationships align with known physiological coupling [5]. Geometric deep learning further situates graph neural networks within a broader agenda of learning from non-Euclidean domains, which is relevant because physiological systems exhibit hierarchical and networked organization [6]. At the same time, wearable systems are not merely computational models; they are embedded in communication networks, power budgets, and user workflows. Internet of Things research has long emphasized that sensing, networking, and actuation must be co-designed rather than optimized separately [1]. This co-design principle is especially important for physical activity monitoring, where real-time feedback may require low-latency edge inference and resilience to intermittent connectivity.

The translational distance between laboratory validation and real-world deployment remains substantial. Health-related machine learning requires careful assessment of clinical utility, generalization, and potential harm [8]. Federated learning architectures offer one pathway to preserve privacy and reduce centralized data aggregation, but they introduce synchronization and data heterogeneity challenges [7]. Moreover, fairness analyses show that sensor-derived datasets can inherit biases from population sampling, device placement, skin tone, body composition, and activity context, leading to uneven model performance [9]. These findings underscore that graph-based physiological models must be understood as components of larger data and governance infrastructures rather than isolated algorithmic artifacts.

3. System Architecture for Graph-Based Multisensor Interaction Modeling

A graph neural network-based physiological monitoring system can be organized into five functional layers: multimodal sensing, edge preprocessing and synchronization, graph construction and relational inference, application reasoning, and feedback or reporting. Within this layered architecture, joint attention mechanisms have been proposed to facilitate opto-physiological monitoring during physical activity by learning to reweight physiological channels under motion-induced distortion [10]. Such mechanisms are particularly relevant in wearable photoplethysmography and electrodermal sensing, where movement artifacts can produce temporary sensor degradation. The architecture must decide where graph inference occurs: on the wearable device, on a smartphone gateway, at the network edge, or in the cloud. Centralized cloud inference simplifies model management but raises privacy, latency, and energy concerns. Edge inference improves responsiveness and reduces data transfer but constrains model size and complexity. System-level design therefore requires balancing inference latency against graph model expressiveness and against the energy budget of battery-powered devices.

The placement of graph construction logic also has structural consequences. In some designs, a fixed graph is computed from anatomical knowledge or from empirical correlations among physiological variables. In others, the graph is learned and can vary across individuals or activity contexts. Learned graph attention mechanisms allow the system to adapt to changing physiological coupling during exercise, recovery, and stress, but they also introduce interpretability and validation burdens. Decision support systems that integrate health data across communities require careful attention to data quality, labeling, and clinical relevance

[11]. High-performance medicine increasingly depends on the convergence of multimodal data and artificial intelligence, but this convergence must be supported by dependable infrastructure rather than isolated model improvement [12]. Multimodal deep learning for activity and context recognition has shown that sensor fusion benefits from architectures that preserve modality-specific structure while enabling cross-modal interaction [13]. A graph neural layer can serve this role by maintaining separate node features for each sensor modality while propagating relational information along edges.

A further architectural trade-off concerns temporal modeling. Physiological interactions during physical activity are not static: heart rate and respiration coupling changes with exercise intensity, electrodermal activity responds to emotional and thermal stimuli, and motion sensors exhibit transient saturations. A graph neural model must therefore combine spatial relational inference with temporal sequence modeling. Some architectures use graph convolutions to extract instantaneous relational features and recurrent or temporal convolutional layers to capture dynamics. Others construct spatiotemporal graphs where time steps are included as nodes or where edges connect sensors across lagged intervals. These design choices affect memory consumption, trainability, and the ability to recover from missing sensor data. The system architecture must also include mechanisms for data imputation, uncertainty estimation, and graceful degradation when one or more sensors become unavailable during vigorous motion or battery depletion.

4. Data Infrastructure and Edge Processing

Scalable deployment of graph-based physiological monitoring requires data infrastructure that can handle heterogeneous sampling rates, missing data, clock drift, and variable connectivity. Deep learning in mobile and wireless networking has provided insights into how inference can be partitioned across devices, edge nodes, and cloud services to reduce latency and bandwidth consumption [14]. These insights are transferable to physiological monitoring, where continuous streaming of high-rate waveforms is often infeasible over constrained wireless links. Hardware-aware machine learning further recognizes that model design must account for memory, energy, and computational constraints of embedded processors rather than treating them as afterthoughts [15]. For graph neural networks, this means that adjacency matrix operations, attention coefficients, and feature transformations must be mapped to hardware efficiently, possibly through pruning, quantization, or the use of simplified message-passing schemes.

Data infrastructure decisions also involve algorithmic ethics and accountability. The ethics of algorithmic systems emphasizes that opacity, bias, and lack of contestability can arise from the design of data pipelines and model deployment rather than solely from the learning algorithm itself [16]. Internet of Things approaches to smart healthcare illustrate how sensing, networking, and decision support can be integrated, but they also reveal challenges in interoperability, security, and maintenance [17]. In physical activity monitoring, these challenges are amplified because devices are worn during motion, exposed to sweat and environmental variation, and used by individuals with different body geometries and skin characteristics. A graph-based model may learn to suppress unreliable sensors or reweight interactions, but if such adaptation is opaque, it can complicate clinical interpretation and patient trust.

Fairness and privacy must be designed into the infrastructure. Algorithmic discrimination can emerge when health-related models trained on one population are applied to another without adequate representational coverage [18]. Differential privacy and secure aggregation methods

provide mechanisms to limit the exposure of individual physiological patterns during model training and data sharing [19]. Federated learning offers a complementary strategy to keep raw sensor data local while updating shared graph model parameters across devices [20]. However, federated training of graph neural networks introduces additional complexity because graph structures may differ across individuals; a lesson learned about heart rate and electrodermal coupling in one participant may not transfer directly to another. System designers must therefore decide whether to share graph connectivity patterns, learn personalized graphs, or maintain population-level priors that are adapted locally.

5. Structural Trade-Offs in Multisensor Graph Modeling

The design of a graph neural network for physiological interaction modeling involves a series of structural trade-offs that shape system behavior in practice. A dense graph permits rich information exchange among all sensor nodes but increases computational cost and may propagate noise from heavily artifact-laden channels to clean ones. A sparse graph reduces computation and improves interpretability but may omit indirect physiological couplings, such as the influence of respiration on heart rate variability through autonomic pathways. Attention mechanisms can mitigate this tension by dynamically sparsifying or reweighting edges based on context, as illustrated by joint attention approaches for opto-physiological monitoring during motion [10]. Nevertheless, learned attention is data-hungry and may overfit to particular motion patterns or sensor placements if not carefully regularized.

Another trade-off involves the granularity of graph nodes. Nodes may represent individual sensor channels, physiological subsystems, or even semantic states such as exercise intensity and thermal comfort. Sensor-level nodes preserve high resolution but produce large graphs that require substantial preprocessing and synchronization. Subsystem-level nodes reduce dimensionality and can incorporate physiological prior knowledge, but they may hide cross-sensor artifacts that are clinically relevant. For example, motion-induced noise in photoplethysmography and electrocardiographic signals can be highly correlated; modeling this correlation at the sensor level may help the system suppress artifacts before they contaminate derived heart rate estimates [10]. In contrast, modeling at the level of abstract physiological states may improve interpretability for clinicians but reduces the system's ability to localize failures.

Temporal resolution is equally important. Physical activity produces rapid changes in motion signals, while electrodermal and thermal responses evolve more slowly. A fixed graph across time may fail to capture the transient coupling between respiration and heart rate during interval training or recovery. Spatiotemporal graphs introduce time-lagged edges that allow information to flow across different time scales, but they increase memory requirements and complicate online inference. The choice between event-triggered and continuous graph updates also affects energy consumption. Event-triggered inference may preserve battery life by activating graph computations only when significant motion or physiological changes are detected, but it risks missing subtle transitions. Continuous inference provides more consistent monitoring but may be unsustainable on limited power budgets.

6. Governance, Fairness, and Policy Implications

Graph neural network-based physiological monitoring operates in a governance environment shaped by medical device regulation, data protection law, and professional clinical accountability. Responsible machine learning frameworks call for prospective evaluation, stakeholder engagement, and clear pathways for clinical oversight when models influence

care [8]. A graph-based system that learns dynamic sensor interactions may be harder to inspect than a fixed threshold model, but it may also provide richer explanations if attention weights can be linked to physiologically meaningful coupling. Governance structures should therefore require documentation of graph construction assumptions, training populations, sensor placement protocols, and failure modes. Without such documentation, the system becomes difficult to audit and may not meet regulatory expectations for medical-grade decision support.

Fairness considerations are particularly salient because physiological signals are affected by skin pigmentation, body composition, age, sex, fitness level, and comorbidities. Optical sensors may perform differently across skin tones, and electrodermal baselines can vary with hydration and ambient temperature. If graph models are trained predominantly on young, healthy participants engaged in controlled exercises, their learned interaction patterns may not generalize to older adults or patients with autonomic dysfunction. Fairness-aware evaluation should examine performance across intersecting subgroups and across different activity contexts, not only aggregate accuracy [9][18]. Differential privacy and federated learning can reduce some privacy risks, but they do not automatically resolve fairness problems; indeed, federated optimization may unintentionally overweight data from users with more frequent device use, thereby amplifying representation gaps [20].

Policy mechanisms can support trustworthy deployment through interoperability standards, certification requirements, and public oversight. Interoperability standards for wearable physiological data would allow graph models to be evaluated across devices from different manufacturers, reducing vendor lock-in and improving transparency. Certification frameworks should require evidence of robustness to sensor loss, motion artifacts, and environmental variation before graph-based models are deployed in clinical or occupational settings. Governance should also address the lifecycle of algorithms, including mechanisms for post-market surveillance and model updates [8]. The algorithmic ethics literature emphasizes that accountability can be weakened when decisions are distributed across many components and organizations [16]. In graph-based physiological monitoring, this distributed character is particularly pronounced because models may be trained in one institution, tuned on another, and executed on consumer devices with different sensing capabilities. Algorithmic accountability therefore requires not only transparent model documentation but also traceable data provenance, clear model versioning, and post-deployment monitoring that can detect performance drift as hardware ages or populations shift.

Meaningful informed consent is complicated by the fact that graph models may infer unmeasured variables such as fatigue or emotional state from interactions among sensors. This raises questions about the scope of consent when secondary inferences exceed the original purpose of data collection. Governance frameworks should require plain-language explanations of what the system may infer and how those inferences could be used by employers, insurers, or wellness programs. The development of responsible artificial intelligence in medicine has highlighted that ethical commitments cannot be satisfied solely by technical accuracy; they must be embedded in institutional review, data access agreements, and remediation processes [8]. Similarly, the algorithmic ethics literature warns that seemingly neutral optimization can produce morally significant outcomes when deployed in high-stakes settings [16]. A graph-based physiological monitoring system is not exempt from these dynamics merely because it uses wearable sensors rather than clinical records.

Policy mechanisms for interoperability and certification are also essential. Health data generated by wearable devices must eventually integrate with electronic health records, clinical workflows, and public health reporting systems. Health information exchange has long faced persistent organizational and semantic challenges, including inconsistent data definitions, competing institutional priorities, and fragmented consent practices [24]. Graph-based physiological monitoring adds further complexity because learned interaction graphs are not standardized data elements. A clinician receiving a model-generated alert may have little understanding of whether the alert was driven by electrodermal changes, motion artifacts, or a combination of both. Certification frameworks should therefore require that graph-based models expose a minimal set of human-readable outputs describing sensor availability, estimated uncertainty, and the most influential physiological interactions. This form of contestability is necessary for accountability in clinical and occupational contexts.

7. Deployment Sustainability and Lifecycle Considerations

Deployment of graph-based physiological monitoring in everyday physical activity settings raises sustainability questions that go beyond energy consumption. The lifecycle of wearable sensors, edge gateways, and model updates involves material resources, software maintenance, and continuous validation. A system may perform well in a research study but degrade as sensor batteries age, adhesives wear, or firmware is updated across a heterogeneous device fleet. Systematic reviews of deep learning in medical contexts have shown that external validation and prospective evaluation are often lacking, leading to optimistic performance estimates that do not reflect deployment conditions [21]. For graph-based models, this problem is amplified because learned interaction graphs may be sensitive to sensor placement, sampling rate, and motion artifact distributions that differ across device generations and user populations. Lifecycle management should therefore include periodic revalidation, regression testing on representative subgroups, and defined triggers for model retirement or retraining.

Sustainable deployment also depends on the relationship between edge and cloud resources. Smart health architectures have long recognized that disease prediction and continuous monitoring require coordinated edge-cloud intelligence rather than a rigid choice between local and remote processing [23]. In graph-based physiological monitoring, lightweight edge models can perform immediate anomaly detection and sensor reliability estimation, while more expressive cloud or server-side models can refine interaction graphs and update population-level priors. This division of labor can reduce communication load and improve battery life, but it also creates synchronization and versioning challenges. When the cloud model is updated, edge models must be updated in a controlled way to avoid sudden changes in behavior that confuse users or undermine clinical trust. The need for semantic and organizational coordination across distributed health information systems has been recognized as a persistent challenge in health informatics [24]. These lessons apply directly to multisensor physiological platforms, which must integrate data across devices, electronic health records, and patient-reported outcomes without losing provenance or interpretability.

Human factors and interaction design are equally part of deployment sustainability. Guidelines for human-AI interaction emphasize that users need clear feedback, graceful failure handling, and control over automation [25]. In physical activity monitoring, users may include patients, athletes, clinicians, and remote caregivers, each with different expectations and tolerance for false alarms. A graph-based model that suppresses a noisy sensor during running but later fails to report a cardiac anomaly may be technically adaptive but operationally confusing. The system should therefore present uncertainty and sensor status in

an interpretable manner, allowing users to understand when inferences are based on reduced or degraded information. Interpretability methods originally developed for tabular and image models can be adapted to graph attention mechanisms, providing local explanations of which physiological interactions contributed to a given prediction [22]. Such explanations are not only useful for clinicians; they also support user trust and informed decision-making about whether to continue an activity or seek medical attention.

8. Conclusion

Graph neural network-based modeling introduces a relational turn in multisensor physiological monitoring during physical activity. By representing sensors and physiological subsystems as nodes with learned or predefined interactions, these models can capture coordinated autonomic, respiratory, and motion-related dynamics that conventional channel-concatenating architectures tend to obscure. The system-level discussion presented here has argued that the success of such models depends on more than architectural novelty. It requires careful attention to data infrastructure, edge processing, graph construction choices, temporal integration, fairness, privacy, and governance. The structural trade-offs between dense and sparse graphs, learned and fixed connectivity, local and centralized inference, and continuous and event-triggered processing shape the behavior, robustness, and interpretability of the resulting system.

The integration of joint attention mechanisms for opto-physiological monitoring during motion illustrates how context-dependent reweighting can improve resilience to artifacts [10]. However, such mechanisms must be embedded within a broader socio-technical framework that includes transparent documentation, post-market surveillance, and equitable representation in training data. Federated learning and differential privacy offer useful tools, but they do not substitute for institutional accountability and user-centered design. The future development of graph-based physiological monitoring will likely move toward personalized and adaptive graphs, edge-cloud co-inference, and standardized evaluation protocols that account for sensor heterogeneity and population diversity. Achieving this vision requires interdisciplinary collaboration among signal processing researchers, machine learning engineers, clinicians, regulators, and patient communities, along with sustained attention to the ethical and governance dimensions of continuous physiological sensing.

References

1. Atzori, L., Iera, A., & Morabito, G. (2010). The Internet of Things: A survey. *Computer Networks*, 54(15), 2787–2805. <https://doi.org/10.1016/j.comnet.2010.05.010>
2. Ordóñez, F. J., & Roggen, D. (2016). Deep convolutional and LSTM recurrent neural networks for multimodal wearable activity recognition. *Sensors*, 16(1), 115. <https://doi.org/10.3390/s16010115>
3. Wu, Z., Pan, S., Chen, F., Long, G., Zhang, C., & Yu, P. S. (2021). A comprehensive survey on graph neural networks. *IEEE Transactions on Neural Networks and Learning Systems*, 32(1), 4–24. <https://doi.org/10.1109/TNNLS.2020.2978386>
4. Veličković, P., Cucurull, G., Casanova, A., Romero, A., Liò, P., & Bengio, Y. (2018). Graph attention networks. In *International Conference on Learning Representations*. <https://openreview.net/forum?id=rJXMpikCZ>
5. Shuman, D. I., Narang, S. K., Frossard, P., Ortega, A., & Vandergheynst, P. (2013). The emerging field of signal processing on graphs: Extending high-dimensional data analysis

- to networks and other irregular domains. *IEEE Signal Processing Magazine*, 30(3), 83–98. <https://doi.org/10.1109/MSP.2012.2235192>
6. Bronstein, M. M., Bruna, J., LeCun, Y., Szlam, A., & Vandergheynst, P. (2017). Geometric deep learning: Going beyond Euclidean data. *IEEE Signal Processing Magazine*, 34(4), 18–42. <https://doi.org/10.1109/MSP.2017.2693418>
 7. McMahan, H. B., Moore, E., Ramage, D., Hampson, S., & Agüera y Arcas, B. (2017). Communication-efficient learning of deep networks from decentralized data. In *Proceedings of the 20th International Conference on Artificial Intelligence and Statistics*, 54, 1273–1282. <http://proceedings.mlr.press/v54/mcmahan17a.html>
 8. Wiens, J., Saria, S., Sendak, M., Ghassemi, M., Liu, V. X., Doshi-Velez, F., ... & Goldenberg, A. (2019). Do no harm: A roadmap for responsible machine learning for health care. *Nature Medicine*, 25(9), 1337–1340. <https://doi.org/10.1038/s41591-019-0548-6>
 9. Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, 366(6464), 447–453. <https://doi.org/10.1126/science.aax2342>
 10. Zheng, X., Hu, S., Dwyer, V., Barrett, L., & Derakhshani, M. (2026). Joint attention mechanism learning to facilitate opto-physiological monitoring during physical activity. *Biomedical Signal Processing and Control*, 113, 108949.
 11. He, J., Baxter, S. L., Xu, J., Xu, J., Zhou, X., & Zhang, K. (2019). The practical implementation of artificial intelligence technologies in medicine. *Nature Medicine*, 25(1), 30–36. <https://doi.org/10.1038/s41591-018-0307-0>
 12. Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine*, 25(1), 44–56. <https://doi.org/10.1038/s41591-018-0300-7>
 13. Radu, V., Tong, C., Bhattacharya, S., Lane, N. D., Mascolo, C., Marina, M. K., & Kawsar, F. (2018). Multimodal deep learning for activity and context recognition. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 1(4), 157. <https://doi.org/10.1145/3161174>
 14. Zhang, C., Patras, P., & Haddadi, H. (2019). Deep learning in mobile and wireless networking: A survey. *IEEE Communications Surveys & Tutorials*, 21(3), 2224–2287. <https://doi.org/10.1109/COMST.2019.2904897>
 15. Sze, V., Chen, Y.-H., Yang, T.-J., & Emer, J. S. (2017). Efficient processing of deep neural networks: A tutorial and survey. *Proceedings of the IEEE*, 105(12), 2295–2329. <https://doi.org/10.1109/JPROC.2017.2761740>
 16. Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. *Big Data & Society*, 3(2), 1–21. <https://doi.org/10.1177/2053951716679679>
 17. Islam, S. M. R., Kwak, D., Kabir, M. H., Hossain, M., & Kwak, K.-S. (2015). The Internet of Things for health care: A comprehensive survey. *IEEE Access*, 3, 678–708. <https://doi.org/10.1109/ACCESS.2015.2437951>
 18. Barocas, S., & Selbst, A. D. (2016). Big data's disparate impact. *California Law Review*, 104(3), 671–732. <https://doi.org/10.15779/Z38BG31>

19. Dwork, C. (2008). Differential privacy: A survey of results. In M. Agrawal, D. Du, Z. Duan, & A. Li (Eds.), *Theory and Applications of Models of Computation*, 4978, 1–19. Springer. https://doi.org/10.1007/978-3-540-79228-4_1
20. Rieke, N., Hancox, J., Li, W., Milletari, F., Roth, H. R., Albarqouni, S., ... & Cardoso, M. J. (2020). The future of digital health with federated learning. *NPJ Digital Medicine*, 3, 119. <https://doi.org/10.1038/s41746-020-00323-1>
21. Liu, X., Faes, L., Kale, A. U., Wagner, S. K., Fu, D. J., Bruynseels, A., ... & Denniston, A. K. (2019). A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: A systematic review and meta-analysis. *The Lancet Digital Health*, 1(6), e271–e297. [https://doi.org/10.1016/S2589-7500\(19\)30123-2](https://doi.org/10.1016/S2589-7500(19)30123-2)
22. Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. In *Advances in Neural Information Processing Systems*, 30, 4765–4774. <https://proceedings.neurips.cc/paper/2017/hash/8a20a8621978632d76c43dfd28b67767-Abstract.html>
23. Chen, M., Hao, Y., Hwang, K., Wang, L., & Wang, L. (2017). Disease prediction by machine learning over big data from healthcare communities. *IEEE Access*, 5, 8869–8879. <https://doi.org/10.1109/ACCESS.2017.2694446>
24. Vest, J. R., & Gamm, L. D. (2010). Health information exchange: Persistent challenges and new strategies. *Journal of the American Medical Informatics Association*, 17(3), 288–294. <https://doi.org/10.1136/jamia.2010.003673>
25. Amershi, S., Weld, D., Vorvoreanu, M., Fourney, A., Nushi, B., Collisson, P., ... & Horvitz, E. (2019). Guidelines for human-AI interaction. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–13. <https://doi.org/10.1145/3290605.3300233>