# Guest Editorial Trustworthy and Collaborative AI for Personalised Healthcare Through Edge-of-Things

FROM diagnosis to therapies, the development of artificial intelligence (AI) has facilitated improvements in personalised healthcare applications. The evolution of AI in healthcare is closely related to the changes in the types and volumes of data which we need to deal with. The first generation of healthcare technologies, represented by the highly successful relational databases, are designed to handle structured data involving patient demographics, patient care, treatments, and outcomes of those treatments. Big Data platforms, which are representative of the current mainstream healthcare technologies, are built to process unstructured data from sources like electronic health records, medical imaging, genomic sequencing, and pharmaceutical research. The next generation of healthcare technologies will potentially be Edge-of-Things data, represented by massive amount of streaming data generated from Internet-of-Things frameworks, Cloud systems, and Edge computing platforms.

AI has achieved remarkable success in the area of personalised healthcare thanks to the vast volume and variety of data from Big Data platforms. Making decisions based on clinical data, for instance, can help clinicians deliver accurate diagnoses and efficient treatments. In certain circumstances, such as when working in intensive care units, real-time decision-making by AI is beneficial for lowering physicians' mental stress. Along with Big Data, the quick growth of Edge-of-Things is promoting cutting-edge AI research in the healthcare domain. Edge-of-Things-based AI for personalised healthcare will pave the way for intelligent health-related applications on edge devices, including wearables and smart sensors. Interactive virtual agents can process personal health data, such as biosignals, acquired by edge devices for providing health status reports and suggestions to individuals. Health data can also be transferred to clinicians for the purposes of establishing diagnoses of diseases, developing personalised treatment plans, and monitoring health status of patients.

In this context, the traits of trust and collaboration in AI systems are very advantageous for providing personalised healthcare services with AI. Particularly, the variety and complexity of these data necessitate the development of cutting-edge AI models and technologies that are capable of processing and analysing them in a trustworthy and collaborative manner. Trustworthy and collaborative AI is intended to encourage transparent, reliable, and unbiased AI systems and ensure these systems are sufficient to address predictive and prescriptive healthcare issues. Such AI systems need to be able to comprehend the issues, determine how to solve the resulting issues, incorporate human intelligence in the discovery process, and then take what they have learnt to tackle those challenges and save the learnt knowledge for the future use in order to be trustworthy and cooperative.

The intended focus of this special issue is the advancements in all state-of-the-art trustworthy and collaborative AI techniques for personalised healthcare. The presented five papers are intended to tackle a variety of research challenges in the area of personalised healthcare, from Big Data to the Edge-of-Things. The five papers explore various meaningful and interesting sub-topics, including model architectures, model explainability, user privacy, and human-machine collaboration.

Electroencephalogram signals (EEG) have been demonstrated to be non-invasive, low-cost, and wearable for analysing brain activities. The first paper by Chang et al. [A1] proposes attention-based sparse graph convolutional neural networks to distinguish between patients with Parkinson's disease (PD) and healthy controls (CTL) using EEG signals. In particular, the graph convolutional neural networks grasp the global feature relationship between EEG electrodes; the attention mechanism estimates the contribution of each electrode to the final predictions; and the sparse constraint is applied to the attention mechanism for choosing significant electrodes. This study investigates two tasks of recognising two PD groups from CTL, namely PD ON (after receiving the drug) and PD OFF (once withdrawing the drug after 15 hours overnight). The experiment results indicate that the attention mechanism makes the model explainable. According to the average attention maps, contralateral frontal lobe concentration distribution or a lateralisation phenomenon distinguish the EEG activity in the PD groups from that of the normal group. Young patients (less than 70 years old) in the PD ON state have higher false positive rates than those in the PD OFF state, which may indicate better remission of PD on medication. The research findings in this work are valuable for creating AI applications in the medical sector for diagnosing and treating PD.

For early detection of cardiovascular disorders, the second paper by Gao et al. [A2] suggests a multi-resolution deep learning model for learning both local and global information from electrocardiogram (ECG) data. This study also employs continual learning (CL), namely ECG-CL, to train a model for multiple tasks, including single- and multi-lead segmentation, and minority- and multi-class classification tasks. The ECG-CL can effectively increase the size of training data and learn inter-task knowledge. The suggested method has demonstrated its efficacy and superiority on both ECG segmentation and classification tasks when compared to the state-of-the-art approaches. The study looks at using continual learning to train a single model in multiple experiment settings with the consideration of real-world applications. Particularly, the experiments of using continual learning to train a model from single-lead segmentation to classification confirms the feasibility of using a single model in wearable technology.

The third paper by Wang et al. [A3] discusses using an interpretable hierarchical multimodal neural network framework (iHMNNF) to make an early diagnosis of fever of unknown origin (FUO). The proposed iHMNNF is built with a top-down hierarchical reasoning framework, five local attention-based multimodal neural networks (La-MNNs), and an interpretable module with layer-wise relevance propagation and attention mechanism. The diagnosis of FUO is done based on the multimodal clinical data that has been gathered, including tabular data, clinical notes, and time series data. The proposed approach is shown to make comprehensive and precise predictions for diagnosing FUO. Additionally, the work analyses the model's effectiveness across a range of lengths of time series data, which is helpful for applying the model to data with suitable time duration in real-world scenarios. In comparison to models with flat structures, the hierarchical model structure is more understandable and accessible because it is consistent with diagnostic reasoning logic of clinicians. The interpretability enhancement provided by the interpretable module is beneficial for human-centred applications in real world conditions.

Personal medical services on edge devices in the context of collaborative learning face a range of challenges, such as data sparsity on individual devices, heterogeneous models brought on by device differences, asynchronous participation of edge devices, and privacy leakage. The fourth paper by Ye et al. [A4] focuses on a novel heterogeneous asynchronous framework termed similarly-quality-based messenger distillation (SQMD) to tackle the aforementioned challenges. When a medical service is running on a shared server and multiple clients (individual devices), the SQMD enables each client to train alternative model structures and distill knowledge from peers through messengers (i.e., the predicted probabilities) with the aid of a reference dataset. The server is able to create a dynamic collaboration graph based on messengers thanks to the SQMD. In the experiments, the SQMD outperforms all baselines, and has demonstrated its robustness in the asynchronous circumstances. The study offers an effective and promising solution for real-life medical applications on edge devices, especially when it comes to managing various server-client interaction scenarios and safeguarding users' privacy.

The final paper by Uddin et al. [A5] proposes a cooperative learning framework to address the challenge posed by the dearth of annotated data in the task of pain assessment. The suggested methodology requests human annotations for data samples with high uncertainty, and employs model-based annotations for samples with low uncertainty. The training data is enhanced in this way by human annotation and machine labelling. A collected dataset with multimodal body moving data categorised into three pain levels is employed to test the proposed cooperative learning framework. The experiments has shown that cooperative learning enhances the collaboration between the model and human, and predict pain with higher performance than the state-of-the-art.

Each of the five papers tackles a different yet crucial research question in the area of personalised healthcare. The advanced and cutting-edge technologies are presented in the special issue, including algorithms, implementations, and applications. We believe this special issue will encourage research development for constructing trustworthy and collaborative AI in personalised healthcare, and inspire commercial development of real-world applications and products, supporting the trend of establishing a new era of AI-powered healthcare systems. We would like to express our gratitude to all of the authors who submitted their research to the special issue. Additionally, we would like to thank all of the research professionals who have contributed to the review process. They offered the authors insightful comments and constructive suggestions for improving the articles' presentation and content. Last but not least, we would like to express our sincere gratitude to Professor Dimitrios I. Fotiadis, the Editor-in-Chief, and the publishing team for their assistance and invaluable suggestions during the challenging stages of concluding the special issue.

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## APPENDIX
## RELATED ARTICLES

[A1] H. Chang, B. Liu, Y. Zong, C. Lu, and X. Wang, "EEG-based Parkinson's disease recognition via attention-based sparse graph convolutional neural network," *IEEE J. Biomed. Health Inform.*, early access, Jul. 05, 2023, doi: 10.1109/JBHI.2023.3292452.

[A2] H. Gao, X. Wang, Z. Chen, M. Wu, J. Li, and C. Liu, "ECG-CL: A comprehensive electrocardiogram interpretation method based on continual learning," *IEEE J. Biomed. Health Inform.*, early access, Sep. 15, 2023, doi: 10.1109/JBHI.2023.3315715.

[A3] Z. Wang et al., "Integrating medical domain knowledge for early diagnosis of fever of unknown origin: An interpretable hierarchical multimodal neural network approach," *IEEE J. Biomed. Health Inform.*, early access, Aug. 7, 2023, doi: 10.1109/JBHI.2023.3306041.

[A4] G. Ye, T. Chen, Y. Li, L. Cui, Q. V. H. Nguyen, and H. Yin, "Heterogeneous collaborative learning for personalized healthcare analytics via messenger distillation," *IEEE J. Biomed. Health Inform.*, early access, Feb. 22, 2023, doi: 10.1109/JBHI.2023.3247463.

[A5] M. T. Uddin, G. Zamzmi, and S. Canavan, "Co-operative learning for personalized context-aware pain assessment from wearable data," *IEEE J. Biomed. Health Inform.*, early access, Jul. 13, 2023, doi: 10.1109/JBHI.2023.3294903.