AI FOR FUTURE HEALTHCARE

Theme Development Workshop

Organising Committee:

Report on the key findings from the Theme Development Workshop "AI for Future Healthcare"

– January 2022 –

Executive Summary

The third Joint Theme Development Workshop (TDW) co-organised by CLAIRE, TAILOR and VISION[1] on "AI for Future Healthcare" took place on the 16th December 2021 with the aim to develop and identify the most promising and emerging AI topics in the healthcare sector. At this one-day workshop, experts from academia, industry and politics jointly developed initial input for the European Artificial Intelligence (AI) research and innovation roadmap. Inspired by introductory speeches and presentations from selected experts, the participants actively discussed a wide variety of topics during the breakout sessions and shared their main results in the subsequent plenary presentations. Furthermore, some initial ideas for follow-up activities and further collaborations have been identified.

This report contains a summary of the results from the Theme Development Workshop "AI for Future Healthcare". To make the results available to a broader audience and the European AI community in particular, this report will be published via the organiser's websites.

[1] In alphabetical order.

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Introduction

In September 2020, four new AI networks were established by the European Commission via the call "Towards a vibrant European network of AI excellence centres" (ICT-48-2020). The aim of these networks is to foster the collaboration between the best research teams in Europe, and to address the major scientific and technological challenges in the field of AI. These four networks are coordinated and supported by the VISION project to foster activities that reach critical mass and enable the creation of a world-class AI ecosystem in Europe.

One of these activities are so-called Theme Development Workshops (TDWs), an innovative format bringing together key players from industry, academia and politics to jointly identify the key AI research topics and challenges in a certain area or for a specific industry sector. In December 2020, an agreement was made between the respective coordinators and leadership teams of TAILOR, VISION, HumanE-AI-Net and CLAIRE to plan and execute a series of Joint (co-organised) Theme Development Workshops, starting in 2021. This report is a result of the third Joint TDW organised and executed within the framework of this series of workshops.

Keynotes and introductory presentations

The TDW was opened by the Co-Chairs Ricardo Chavarriaga and José M. Sempere on behalf of the Organising Committee (OC), which included further representatives from CLAIRE, DFKI, LIH, NTT Data, Philips, VRAIN and ZHAW. The Co-Chairs outlined the objectives of the TDW as well as the agenda and programme, and introduced the invited keynote speakers to the participants.

The inspiring keynotes were provided by high-level experts from several European countries. These introductory presentations served as a basis for the discussions about Trustworthy AI for Future Healthcare, data sharing in the Healthcare sector and Explainable AI. Accordingly, these presentations stimulated the expert discussions in the following breakout sessions.

Introductory presentations by Prof. Dr. Ulf Nehrbass, Dr. Alfonso Valencia, Dr. Nicola Pezzotti and Anna Forment.

Prof. Dr. Ulf Nehrbass - Luxembourg Institute of Health

In his keynote, Prof. Dr. Ulf Nehrbass from the Luxembourg Institute of Health (LIH) presented the Clinnova project. The Clinnova project consists of a large network with partners from Luxembourg, Metz/Nancy, Strasbourg, Basel, Mannheim, Saarbrücken and Freiburg with the strategic goal to unlock the potential of data science and AI in healthcare, i.e. with better data driven methods, increase in diagnostics efficiency, precision medicine, medico economic savings, opening prevention effort and better patient care. Clinnova considers AI innovation in healthcare an operational and organisational challenge where the key innovation driver is not the AI algorithm but the data-enabling environment that produces standardised and quality-controlled data around relevant use cases. Clinnova's concept is based on data quality by producing standardised and quality-controlled data in prospective cohorts, straightforward AI algorithms for patients stratification to train on structured and clean data, as well as progressively extending the use of trained AI algorithms into retrospective data. Therefore, Clinnova's prospective studies start with 3 medical use cases, namely Inflammatory Bowel Disease (IBD), Rheumatoid diseases (RD) and Multiple Sclerosis (MS). These use cases put physicians and patients in the centre on a short- and medium-term scale by assigning the right and personalised medication to the physicians and patients who make data available and data analyses will generate insights into biomarkers and drug targets. In each case, multidimensional data is collected and stored in a central biobank. The use of multiplexed AI-driven stratification endpoints enables functionally relevant personalised stratification of patients driven by the drug. In terms of data and security, Clinnova adheres to GDPR and strict privacy regulations in Europe. Also, by building a federated data environment, methodologies will be evolved that reconcile analytic efficiency with security and trust. This approach will then assure international competitiveness in the medium and long term. To facilitate trans-border flows and collaboration, several data integration systems are in place and different specialists ensure seamless interoperability across the borders. Another similar approach by Clinnova for precision medicine in cancer is the development of a Functional Patient Profiling (PFP) that generates personalised treatment options within four to six weeks. The PFP produces patient specific treatment choices and is also a fast track to annotating patient genomic data and allows a correlation with high resolution tumour images.

Dr. Alfonso Valencia - Barcelona Supercomputing Center

The second keynote was presented by Dr. Alfonso Valencia on open questions in the topic of AI, genomics and personalised medicine. The path for precision or personalised medicine generally consists of a computational infrastructure, like databases, methods, systems and resources to perform the analysis of the data. The two following components are the research environment, like epigenomics, proteomics or metabolomics and the clinical environment, like epidemiology, medical devices or medical images. Both components are required for the interpretation of the data and consequently the multi-omic report that is helping the patient. In general, Genomic (OMIC) data is fast growing and heterogeneously produced by different technologies in many cases by small providers. The data is often very noisy and complex due to experimental samples and complex biological and data-related circumstances. Also, genomic data is interlinked and personal due to sensitive personal information. The main challenges for this sector are quality standards (accreditation), common analysis standards and pipelines as well as data sharing in terms of federated access, discovery systems and federated learning. Medical data (EHRs) have the same properties as Genomic data but are not growing as fast. The main challenges are how to access and extract information in terms of security, NLP, images and other non-structured sources, ontologies and data normalisation as well as the semantic interoperability. As for the infrastructure layers, there are still various discussion points, like core databases versus project sites (IDs in the cloud), computing continuum where systems have to be run in pairing devices and pairing clusters, i.e. in hospitals. Furthermore, there are challenges of academic versus commercial cloud providers, protected work environments, benchmarking and certification systems as well as security and transparent access. For the interpretation and implementation, several aspects have to be taken into account, for example, interpreting the data is needed with different existing data analysis systems for different area specific systems, i.e. Tumour Board portals. Also, the data integration and data fusion, meaning different ways of putting data together, can be a challenge for data interpretation and user layers. The same goes for simulations and AI/ML as black boxes in terms of biases in the systems and the required explainability for the certification of a system and support systems as well as human decisions. On the patient layer for medical systems, the key challenges include the adoption of medical systems, especially in regard to the evaluation and the approval systems, agencies and medical guidelines. Apps and software integrated in the system have to be evaluated in forms of certification and commercialisation. What it needs in particular is the patient's control of the data. Further challenges include the inequality and biases of the data, training and, of course, the participation of patients and citizens.

Dr. Nicola Pezzotti - Senior Scientist AI from Philips Research

In his keynote, Dr. Nicola Pezzotti, Senior Scientist Ai from Philips research, showcased AI use cases in the Healthcare Industry that have already been deployed within Philips. It is Philips' overall purpose to improve people's health and well-being through meaningful innovation by improving the lives of 2.5 billion people per year by 2030. To achieve this goal Philips developed a concept called the "health continuum" which is basically the idea that health is not only about diagnosis and treatment but rather starts with the aspects of Healthy living (Personal Health) to the prevention (e.g., Precision Diagnosis and Image Guided Therapy), Diagnosis and Treatment and the After care at peoples home. Across this continuum, patients and customers are supported by the development of solutions by Philips at the respective stages. One thing that has become apparent in recent years, especially in the healthcare sector is that AI plays an important role across these phases. Before Dr. Nicola Pezzotti proceeded with the specific use cases he outlined the application of AI and especially the commitment of Philips to the responsible use of data and AI. To ensure the ethical use of data they diligently apply the principles of Security, Privacy and beneficial use of data. In addition to these Data Principles, Philips embraces the AI Principles of Health and weel-being, Human oversight, Robustness, Fairness to avoid bias and dicrimination and Transparency. The value of AI is only as strong as the human experience it supports, which means that Philips wants to have Ai integrated in the whole workflow. They are combining the power of AI with deep clinical knowledge to create solutions that integrate AI into the workflows of healthcare providers and people's daily health routines to support them at every stage of the health continuum. Regarding diagnosis and treatment there is another continuum where AI plays an integral role from Scheduling and preparation to Image acquisition, Image Interpretation, Reporting of the results and communicating, Shared decision making and also the outcome definition. Dr Nicola Pezzotti presented specific use cases for each of these areas in order to explain them in more detail. For this purpose he started with the area of Scheduling and preparation by showing the example of an MR, where an additional camera is added to the system that is directed at the patient in the MR scanner for the Respiratory triggering and breath hold monitoring as well as automatic respiratory triggering and gating patient respiration through the use of an AI system. In the past, a so-called respiratory belt was often used for this purpose. Compared to the AI-based use of the camera (VitalEye), however, it has been shown that a much higher quality of images can be achieved by using the VitalEye. Another example of AI usage which he mentioned in his keynote is the automatic patient positioning and scan planning in the CT-scan. This system automatically selects patient orientation in prone or supine position and also selects survey start and end position with no need for manual adjustment and thus does not require further scanning due to repositioning. A further example of AI usage relates to the fast MRI challenge, based on which Philips was able to develop their new SmartSpeed product which integrates AI into MRI scanners. AI has also frequently been used in work-flow optimisation in hospitals and most impressively in fully automatic image analysis of chest CT scans. Furthermore, Dr. Nicola Pezzotti highlighted datasets and annotations as the biggest challenge. Lastly, he concluded that AI can augment the expertise of healthcare professionals, improve operational efficiency, that human experience must always be put first, that deep knowledge and AI techniques together are the best approach, that novel approaches can help scale the use of AI in healthcare, and that monitoring performance and impact in the real world will be key to mature as an industry.

Anna Forment - Director Health & Public Sector , NTT Data

The fourth keynote, held by Anna Forment from NTT Data, was about how AI can be applied in the healthcare sector to improve management of healthcare systems. First, she noted that all European health institutions, from the political institutions under the umbrella of the European Commission to the national health and social institutions, need to focus on using data to compare in a specific knowledge to make health systems more efficient. With regard to the global approach, she explains the fields where AI can support healthcare management and its improvement. The main objectives of the healthcare systems are to make estimations and predictions about population health and care needs, to direct the healthcare to a person data centric approach, to guarantee the sustainability of the healthcare system and to be resilient and flexible when facing health threats. The three main areas where to apply Artificial Intelligence to healthcare management focus on population health and healthcare services planification, person-centric healthcare and the support of healthcare professionals' decision-making. The population health and healthcare services planification faces three main challenges: how to apply AI to make population segmentation and to use health data and social conditionings in an uneven digitalisation and standardisation ecosystem, the prediction of models for planification based on population data based on individual data, familiar data health records, environment and other as well as prediction needs with regard to health threats using different sources of data to support policy making and management decision-making to make predictions for future situations facing health threats. For person-centric healthcare, the focus is specifically on four areas: advanced diagnosis with a holistic approach, optimising patient selection for specific health programmes, addressing patient monitoring needs and augmenting capabilities with a human interface. With regard to the first area, it is important to include biopsicosocial variables in the diagnosis and to take into account the familiar health history in order to make better prognostics associated with the individual diagnosis. In order to advance in person-centric healthcare and to optimise the patient selection for specific health programmes, it is necessary to improve the accuracy of screenings according to relevant variables and to rethink the preventive protocols. But also addressing patient monitoring needs by personalising care according to the preferences and outcomes and results are an important step towards person-centred healthcare. Finally, adding a human interface to the capabilities where NLP is used to understand both written and spoken language from structured and unstructured data sources to accompany the patient throughout their illness across all healthcare pathways is a good way to move forward. The presentation was concluded with three steps to support healthcare professionals decision-making: supporting decisions with imaging data by starting to implement image data analysis through deep learning capabilities, personalised and precision medicine by using all the information related to the individual's experience and health outcomes and applying genomics across all healthcare pathways and levels of assistance and finally, improving clinical assistance by exploiting clinical record data by leveraging the treatment of clinical records using NLP to make predictions about prognostics and aggravation episodes.

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Key results from the Breakout Sessions[2]

Trustworthy AI for Future Healthcare - Group A

Ricardo Chavarriaga, Frank Broz, Holger Hoos, Dimitris Kalles, Marc Lenz, Manuel López-Ibáñez, John Juls Meyer, Andreas Nonnengart, Anne Schwerk

The breakout session started by identifying key enabling factors of Trustworthy AI in the healthcare sector. Participants rapidly pointed out that **Standards are one of the most important aspects for Trustworthy AI**. Currently, there are several international initiatives aimed at developing governance frameworks that can support AI trustworthiness. These initiatives cover aspects like ethical guidelines, principles for accountability and regulation proposals, but they do not have yet a global dimension and differences can be observed e.g., between the US, China and the EU. Increased efforts in the standard development are necessary, including incentives that promote the involvement of all relevant stakeholders.
The **explainability of the AI models** is a crucial element for gaining the trust of all stakeholders as well as a likely requirement for regulatory compliance. In this respect, significant support is required in the development of methods that allow opening of the black-box. Regarding this, it is important to keep in mind that not all AI systems for healthcare rely on deep-learning techniques and approaches involving hybrid AI may play an important role in the future.
Also important is the availability of **adequate infrastructure for the conception, development, and validation of AI systems**. AI performance is dependent on the processes for data collection, curation and management. Therefore, the trustworthiness of these systems will require suitable, well-resourced infrastructures to efficiently perform these processes in a way that satisfies the performance criteria of service providers, regulators and patients while respecting social and ethical norms.
Involvement of field experts and practitioners is a sine qua non condition for achieving trustworthy AI systems for health. It is worth noticing that the trust of an AI-supported healthcare system will depend on all the elements involved, including the AI systems and practitioners who use them. Hence, p**ractitioners need to be involved as early as possible** in the life cycle of the AI system and be able to spend enough time and resources to understand the capacities and limitations of the AI systems. As such, cultivating a culture where practitioners exert healthy scepticism will be important to better identify the areas where AI can have more significant impact in the health of society, while limiting the risk of feeding the hype cycle and triggering excessive expectations. Multi-Stakeholder collaborations, like the one established by **CLAIRE** and the **Hippo AI Foundation** are a viable approach to facilitate this involvement.
In the foreseeable future the decision-making process in healthcare will remain on the human-side. These decisions will be supported by information inferred by AI-systems. There

[2] Breakout session moderators are highlighted in bold, participants are listed in alphabetical order.

is thus a **need to better understand how decision making and practitioner's behaviour are affected by the introduction of AI-systems.**
As mentioned above, the involvement of practitioners, patients and other multiple stakeholders is required throughout the entire life cycle of the AI systems (covering their conception, development, validation, use and decommission), as well as in the development of standards and governance approaches. It is thus **important to stimulate the formation and career development of professionals who can be a bridge between all stakeholders**. At the immediate level, it is important to identify which are the individuals and organisations that are leading current initiatives in the global sphere and ensure that the EU has a significant contribution.

Trustworthy AI for Future Healthcare - Group B

Freek Bomhof, Sara Colantonio, Norbert Jastroch, Radovan Kavický, Adriano Lucieri, Henninng Müller, Vivek Nallur, Enayat Rajabi, Arthur Schreuder

The breakout session started by identifying that **data quality** is still an important topic that should receive sustained attention. It is still not possible to have widely agreed metrics for data quality. With plans for the European Health Data Space, topics like reusability of data, metadata (provenance), but also detection and mitigation of bias, should all be elaborated.
Not specific for the healthcare sector, but probably the most intricate and tightly related concept is **privacy**. Medical data is very sensitive and exploiting that data to its maximum use will inevitably create tensions between values. **Privacy Enhancing Technologies** are a technological development that can alleviate some of the problems and these need to be developed further. Another important related concept is **sovereignty**, meaning that the involved persons should be given good opportunities for consent management.
Explainability has similar tensions with other values. Not only because associated transparency creates challenges with confidentiality of data, but also because autonomy and agency of users can be challenged when a smart AI gives explanations in a situation where information asymmetry between patient and doctor exists. AI should be able to **mitigate the knowledge gap** between patients and professionals. The main problem with explainability itself is the **lack of a commonly agreed understanding of what 'explainability' is**, how to measure it, how it promotes calibrated trust, and how to assess the quality of an explanation for different user groups. Explainability is an interdisciplinary topic and should have a roadmap of its own.
Another relevant topic is **certification**. This should develop beyond risk minimization and also take performance more and more into account. Apps and software, especially when they contain AI, should be treated like drugs in terms of certification. There was a concern that 'the horse has already left the stable' here, given the large amount of health-related apps that are currently being put on the market already. Just like in the food industry, where ingredients and key data about the food inside the package have to be put on the label, some kind of 'model passport' that informs users could be considered.

Data sharing in the Healthcare Sector

José Aznar, Josep Lluis Arcos, Serge Autexier, Sébastien Daniels, Christoph Lipps, Zoi Rakopoulou, Jacek Ruminski, Ray Walshe, two further participants preferred not to be mentioned publicly by name and affiliation

More and more data is being produced from various sources (e.g., medical devices, smart devices, public records), in different geographies, and is often owned by different parties like academia, hospitals, industry as well as governments. Data sharing can improve AI analysis: The richer the data collection, the more robust and reliable the model will be and it is a reality that a considerable amount of data is required to grant that the training process will have success finding these patterns. Taking this challenging scenario as reference, the breakout Session "Data Sharing in the Healthcare Sector" gathered the expertise of relevant stakeholders – Data owners, data scientists, researchers and lawyers mainly – to discuss and brainstorm on the challenges and benefits of data sharing as well as on the key technologies and enablers currently coming into scene. Most relevant conclusions derived from the discussion and questions triggered by the participants can be summarised as follows:

(1) **GDPR is blocking research unwillingly**. In future there should be more discussion about how to adapt GDPR for research purposes.

(2) **Data Silos** are partially **motivated by the lack of trust in data privacy and security** mechanisms. It is a fundamental right to know what others are doing with your data.

(3) The AI environment claims a number of benefits while **gaining access to Data to train models.** Nevertheless, data owners are sceptical to some extent in the sense that they don't yet see the real benefits of adopting AI in healthcare settings as a counterpart for providing access to data.

(4) With regards to the **inclusion of Real world data and synthetic data** as a means to gain access to larger datasets, these are great approaches that help to train AI, however, it is essential that we have access to the real data.

One thing is clear: „sharing is caring"; and all stakeholders should contribute to address aforementioned challenges and collaborate to make health data really actionable data to leverage on and benefit research, benefit healthcare professionals and carers and far above all patients, real owners of the health data.

Trustworthy AI aspects on time series data analysis

Wico Mulder, Joscha Grüger, Elsa Kirchner, Jan Komorowski, Moritz Thielen, Rien van Leeuwen

In personal, connected and in-hospital care, time series data is a common and important form of input data (e.g., toothbrush localization, sleep phase determination through headphones). This breakout session focussed on important trustworthy AI components, challenges, and solutions for this type of data and its analysis.

The session started with a presentation by Rien van Leeuwen about the development of the Philips Smart Toothbrush, a customer device that works with a mobile app. The challenges that Philips encounters lie at the levels of user adoption as well as on the level of model development. The overall idea is that the app provides feedback about the daily brushing process. At first sight the situation and challenges seem to be **specific** for the product itself. However, the data modelling process as well as the attempts for efficient feedback from the user to the system holds for **other products**, in other markets, as well. In the group **Feedback loops** were found to be key in the process of adoption of the product. For time series data also the **moment of feedback** is important. Not only to improve the process of (technical) data modelling but also for the adoption (and thereby the amount of input data) is important. Another aspect that was mentioned in the discussion was the **combination** of datasets. E.g. brush activity data, safely kept local and group behaviour data. During the session we discussed different time intervals, different contexts and the use of **federated learning** on multimodal/multisensor data and early vs late fusion. From a technical as well as GDPR point of view it is important to think about **similarity**; when is the input similar to samples in a user specific dataset, when is it (significantly) different. Can SSL + clustering help us here? It is challenging to find the **ground truth** with respect to the datasets, and to relate that to unusual/random behaviour. Thereby it keeps challenging to interpret the data, discover outliers, and provide useful feedback to the end user (the brusher). A different approach for increasing further adoption is to **combine different AI apps** for health. This goes in the direction of lifestyle and prevention, where it is often not only one isolated problem that needs to be addressed. The challenges then shift to finding ways to fuse data for better interpretability, thus not only focus on precision, but instead focus on combining data. It is here where the field touches **social implications social interactions.**

At the end of the session the group discussed activities they would like to follow/organise to address the challenges. One one the ideas were to organise a **hackathon / work session** in which experiments with other cases can be compared to identify similarities in the challenges, possibly combine them, and relate them to technical and societal research activities.

Perhaps it is useful to test a different approach in the direction of **persuasion** and coaching Focus more on the social aspects which might lead to better (interpretable) data, and thereby classifiers. Maybe some themed sessions can be held. Also some **practical advice** came from the group: Maybe low(est) hanging fruit: a robust uninterpretable detection that warns you when the input is “different” and therefore network output can not be trusted. Next step would be to make this detector interpretable/less black box. The group coined the term “**brushworthy AI**”.

Trustworthy AI aspects on image segmentation and reconstruction

Christian Schorr, Andreas Fehlner, András Lorincz, Carsten Maletzki, Francesca Pratesi, two further participants preferred not to be mentioned publicly by name and affiliation

Medical imaging is a powerful tool for the diagnostics of diseases. With the advent of AI, classical segmentation algorithms have been replaced by much better performing convolutional neural networks. This development has opened up avenues for automatic image segmentation and reconstruction. Industrial use cases comprise tumour detection in computed tomography or magnetic resonance imaging scans, as well as real-time X-ray image denoising to enable low doses in angiography or image guided surgery. Since the consequences of wrong results often are literally a matter of life and death, the trustworthiness of these AI algorithms is very crucial.

One major long term challenge the break out session identified is the **availability of fully annotated public datasets for image segmentation.** There is always the issue of patient data security which puts restrictions on the use of the data in AI research and applications. Often explicit patient consent has to be asked for to gain access to the data. For some use cases like X-ray image denoising, there simply is no ground truth available because that would mean irradiating patients with different doses simply to get the same picture with different noise levels. That is neither medically nor ethically acceptable.

For data sets with annotations, there is often **the problem of quality**. Experts do not always agree on a single segmentation of a tumour for example, so either several experts have to vote on a given segmentation or the annotated data set could suffer from bias depending on who did the annotation. A possible solution could be quality measure / curated data sets perhaps provided in a GAIA-X context.

An important discussion point was the **general role of AI in medical applications**. Should AI act as a stand-alone medical application or should it be restricted to the role of a decision support system for humans. So far, only systems which support the clinician are commercially available. This is also due to ethical and legal issues when using AI assistance. For low risk use cases like computing sports training advice from smart health watch data the hurdles are much lower than for robotic surgery systems actually operating on a patient. The final responsibility has to stay in the hands of the clinician or the user.

Another type of use case not typically considered when talking about medical image segmentation that came up during discussion is **robot-assisted monitoring** and interacting with a patient during recovery/rehabilitation or during daily routines. From an algorithmic point of view, these machine-assisted therapeutic procedures touch not only upon aspects of computer vision similar to autonomous driving but also on machine-human interaction where the intentions of the patient have to be predicted from their behaviour in order to prevent falls or other injuries.

AI and genomics: Building Precision Medicine using reliable AI

José M. Sempere, Hatice Aldemir, Claudia Angelini, Andreea Avramescu, Alessandrao Bregoli, Adrien Coulet, Yann Le Cunff, Tom Lenaerts, Anna Leon, Carlos Peña, Rubén Saborido, Fabio Stella, Alfonso Valencia

In the breakout session on AI and genomics, reliable AI techniques (especially machine learning and deep learning), and how they support bioinformatics in clinical diagnosis, were discussed and analysed. The integration of information on patients of a diverse heterogeneous nature (genomic, clinical, environmental, ...) was discussed quite extensively. The main conclusions reached regarding this topic was that **new protocols and standards** are needed for the collection of information that takes into account the polyhedral aspects of health and its diseases, and **quality controls** must be implemented to give a minimum reliability of the information collected. Importantly, in the current day and age, this information **includes software as well**, requiring thus AI and ML predictive approaches to adhere to some essential quality principles (e.g. DOME recommendations). Workshops on how **FAIR principles** introduced for scientific data can be extended to ML and AI are underway to fill this gap (e.g.RD alliance).

The importance of collecting information about negative results on clinical experimentation leading to avoid **undesirable biases** in AI systems was also highlighted. In addition, there exists an increasing need to extend the amount of information available in order to integrate the information effectively.

Regarding the methodologies and techniques to carry out the information processing, organised in multiple data repositories with a low information density, **transfer learning** technologies seem to be able to provide successful scenarios in multiple health application domains. These techniques together with a combination of **data-driven and model-based approaches** can be an adequate framework for the development of a successful paradigm of AI applied to health, especially in the field of genomic medicine.

Another fundamental aspect regarding information processing is the **transfer of primary knowledge to secondary knowledge**. In this case, the need to articulate and regulate transparent methods for sharing information was highlighted, as well as the interest in gradually implementing standards for the effective development of a uniform collaboration scenario.

The other main aspect that was discussed in the session was related to the **characteristics that the various AI engines applied to the field of health genomics should have**. In the first place, the simulation of biosystems related to disease and the processes affected by genomic information (from biomolecular processes to digital twins) require new **data-driven methods** and **translation techniques**. These methods and techniques should be able to connect various models at different scales (i.e. from specific biomolecular processes to complex disease pictures). In this case, methods known in other areas of AI, such as multi-agent systems, natural computing (specifically, membrane computing) and other correlation methods should be explored. Similarly, the combination of knowledge-based methods and data-driven models seems to be a promising approach.

Regarding prediction systems, and the application of machine learning techniques, the existence of **black boxes** can compromise the acceptance of these systems in a field of application as sensitive as that of health. A dichotomy is produced since, in the field of genomics and health research, systems with black boxes have proven their usefulness, while in the case of clinical practice, fully explainable AI systems are required for their

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application, as is the case with any other diagnostic tool used today. Ultimately, working in the field of genomics and health should tend to produce AI systems that explain the relationship between genotypes and phenotypes. This should be a leitmotif for AI systems to be produced in this field of application. In any case, the balance between usefulness and explainability should be modulated depending on the task in which the AI engines are used.
Last but not least, the existence of biases in **AI systems applied to genomics and health** should be explored. Some of these biases, due to the biological nature of genomic information, far from being undesirable are necessary. There is a need to study and control the introduction of biases in AI systems that occur in this application area.

AI in infodemics

Pierluigi Sacco, Zakaria Abdelmoiz Dahi, Philippe Thomas, Manlio De Domenico, Vladimír Šucha, three further participants preferred not to be mentioned publicly by name and affiliation

The complex infodemic phenomenon concerns the **overabundance of information**, not necessarily reliable, circulating online and offline about an epidemic outbreak with a huge impact on public health. Therefore the participants of the breakout session “AI in Infodemics” discussed infodemics and the role of AI to assess the **infodemic risk**, with potential applications to public health. Within these discussions it has become apparent that there are 2 main challenges of AI in infodemics that need to be overcome, namely the questions how this phenomenon can be first detected and quantified and how AI analytics can be translated as an output to policy. To inform the policy and also to involve legislators to establish appropriate regulation a **AI assisted risk monitoring and assessment** is required. One of the most relevant results on this topic is the **C19 Infodemic Observatory** that heavily rely on AI techniques and science to make an assessment of the risk of infodemics in collaboration with the infodemic management team from World Health Organization (WHO). They have gathered a unique team of computer scientists, social scientists, and business leaders to gather massive datasets from the private sector in order to provide live and actionable insights for other researchers, policymakers, and the general public, while respecting privacy. The C19 Infodemic Observatory analysed more than 2.2 Billion Tweets and 200 Million URL which led them to the conclusion that only 58% of the content is produced by Humans while 42% is produced by Non-Humans like Social Bots. It has also become apparent that **71% of the content online comes from reliable sources while 29% of the content is not reliable**. In addition to this it is also of utmost importance to recognise the relevance and interdependence with other phenomena, like spreading of the epidemics. Within the discussion of the breakout session the participants gathered some thoughts for follow-up discussions like the question wow to design a new way of communication to provide reliable information able to convey the same emotional payoff of an unreliable information/content? In this case AI plays an important role to scale the solutions. They have also worked out that it would be of great interest for the future research in infodemics to combine insights from **interdisciplinary disciplines** like Computational Social Science, Behavioural Neuroscience, Complexity Science to achieve better results and a broader insight. In addition, the topic of **Trustworthy AI** will play a major role in this area of research in the future by developing trustworthy AI, which will be the key to fight infodemics.

Trustworthy aspects for NLP

Joachim De Greeff, Sara Colantonio, Adrien Coulet, Aki Härmä, Andreas Nonnegart, Enayat Rajabi, two further participants preferred not to be mentioned publicly by name and affiliation

In patient intake and engagement, medical documentation, automatic report generation, EMR analysis and forecasting, NLP is widely used. This breakout session focussed on the most important trustworthy AI components, challenges, and solutions for these use cases.
The group started with a presentation of Aki Härmä from Philips Research, which highlighted some important aspects and questions regarding the use of Trustworthy AI/NLP in healthcare. In particular, they touched upon the topics of Explainable AI, Safety and Robustness, Respect for Privacy, Fairness, Equity, and Justice by Design, Accountability and Reproducibility by Design and Sustainability aspects of large scale utilisation of such systems. This kicked off a broad discussion amongst the workshop participants, in which they tried to define when AI/NLP systems are trustworthy, arriving at the following list of requirements. AI/NLP systems can be considered trustworthy if they are:

- bias-free
- explainable
- inclusive, NLP powered AI for healthcare should be available for all (not just particular language groups)
- securite/privacy-preserving (particularly regarding data sharing)
- support (user) sovereignty
- sustainable

Furthermore, the following key observations were distilled from the breakout discussion:

1. **NLP is an enabling technology**, meaning that it is at the core of a wide range of interaction scenarios within a healthcare environment. It can support making AI solutions explainable, e.g. through dialogue.
2. Language carries a lot of (cultural) information, and as such there exist higher risks for bias. **Bias is everywhere**, and awareness is the first step towards mitigating this (using synthetic data may be one mitigation strategy). Additionally, due to its interactive nature, language/NLP offers an opportunity to remedy (bias) issues through interaction/conversations.
3. **Ambiguity and context understanding are the most challenging aspects for NLP applications**. Ultimately this may require the development of Artificial General Intelligence (AGI). Knowledge graphs can be a powerful tool in helping understanding the context, particularly if these are dynamic, updating knowledge could happen through interaction with users.

4. Proper **data sharing solutions are needed** in support for creating the next generation of Trustworthy NLP systems. These solutions should support the sharing of trained models while preserving privacy. Initiatives such as the European Data Spaces are examples of promising solutions for this. An alternative could be the generation of synthetic data to train models.
5. **Sustainability aspects** are currently an issue, e.g. in terms of energy required for training contemporary NLP models such as BERT. Particularly for scaling up this technology to wide-range application this needs to be solved. Precise definitions of tradeoffs between e.g. energy usage and utility of NLP/AI solutions will aid in this.

Federated learning approaches for the Healthcare sector

Christian Schorr, Zakaria Abdelmoiz Dahi, Hatice Aldemir, Serge Autexier, Daniel Gatica-Perez, Josep Lluis Arcos, Moritz Thielen

The participants of this breakout session discussed and analysed **federated learning approaches to facilitate the analysis of health data** stored across different stakeholders and/or borders. This should, for instance, avoid the transfer or exchange of data and ensure increased security. An industrial use case, where federated learning and preprocessing is performed on devices/smartphones serves as a starting point to discuss the challenges of applying federated learning in real world applications.
One of the first points to keep in mind is that federated learning is a broad concept with algorithmic approaches heavily depending on the actual use case. During the discussion the participants identified two main types: **use cases featuring a few big data silos** (hospitals for example), which are always online and are endowed with sufficient computing power on the one hand and **use cases where many small devices (like wearables or smart phones) are the data sources**, but are only sometimes online and with very limited computing capacity. It is obvious that while both types are federated learning scenarios, their needs and requirements are vastly different and thus require different algorithmic solutions.
A fundamental issue for all use cases is the **legal question of data security and anonymity**. How can these be guaranteed when using federated learning? The ensuing discussion found the **need for a binding legal framework** in which to conduct federated learning. This tied in with the problem, that a precise definition of “Federated learning” is necessary to make sure all stakeholders are aligned on objectives.
A high communication load is required for successful federated learning. This is difficult for low battery distributed devices with low connectivity, so there has to be a tradeoff between communication and computation. How to choose the best trade-off theoretically leads to a **multi-objective optimization problem**, which is hard to solve practically. Making use of sparsification and quantification strategies or a combination thereof could be a way to handle this challenge.
An additional point which has to be taken into account is the **problem of devices dropping on and off due to individual user behaviour**. This causes a **data bias**, because some devices deliver much more data than others, which in turn can skew the federated learning

results. A solution could be the use of **asynchronous training when building the federated learning models**. Assuming that we have successfully trained such a model, then how to evaluate it, since the original data on which it was trained is no longer available? This is especially hard for use cases with many devices (wearables for example), where data is not stored for a longer period of time.

During the discussion the question arose, whether there are any centralised data platforms shared at EU level for federated learning and if not, is the EU planning to put in place such a platform. This illustrates another challenge: the **availability of training data** for federated learning research - quote: "I want to do federated learning, but I don't know where to find data". A solution to the data storage issue could be an European cloud with citizen empowerment for uploading personal health data. This is another aspect which could function as an actual, albeit challenging, use case for GAIA-X. It also shows the need for a central information site, where one can get the data needed, a measure of the data's quality, as well as legal and economic structures like incentives around it.

A final challenge for every federated learning use case is the **standardisation of the input data.** Data acquired through different standards are usually not comparable. Therefore interoperability between data providers is a necessary prerequisite for the subsequent actual federated learning itself.

Explainable AI in Healthcare - Group A

Sven Hirsch, Andreas Fehlner, Carsten Maletzki, Manfredo Atzori, John Juls Meyer, Serdar Özsezen, Francesca Pratesi, Zoi Rakopoulou, Jacek Ruminski

Health data is particularly sensitive and solutions developed with the help of AI are often difficult to understand. The aim of this breakout session was therefore to dive into **explainable AI** to promote the acceptance of digital health solutions in society.

The discussion started with possible reasons that require explainability, with the concept of ethics being particularly emphasised by the participants, as explainability is an essential and important factor in **strengthening human trust** in non-human systems.

Furthermore, another important aspect related to the overarching topic of explainability is the **generalisation of AI models** to ensure the content transfer from one model to another. In the context of medical knowledge, it is also crucial to construct a **common knowledge model** between the technical specialist/engineers and the medical specialists like doctors or medical nurses as well as the **right training in AI** for these groups on how to improve reasoning via assistive diagnostic tools with the help of AI. Also, this presupposes that humans still have the possibility to intervene in the decision-making process of the AI tool at any time.

Another important aspect highlighted by the participants of the breakout sessions is the fact that when considering software as a medical device, the **effectiveness and robustness** of software as a medical device must be proven and ensured. Considering the current situation, it can be determined that the interpretability of data or processes is highly context-dependent. In addition, medical experts are accustomed to black-box systems (i.e.

drugs whose underlying mechanism is unknown, clinicians' own solutions for certain measurements), which in turn is associated with risks. Therefore, there is also a great responsibility to ensure that these instruments are **robust, explainable and trustworthy**.
It was also found that explainability is often not that important for the end user (i.e. the patient, the clinician, the caregiver) as long as the end user benefits from it. In this context, the research has also shown that industry stakeholders are not necessarily interested in creating better (explainable) models and optimising the models.
In terms of the potential for standardising explainability, the relatively slow adoption and acceptance of AI models due to lack of trust can be addressed. There is also the problem that there are no definitions for many medical observations, so explainability can also be a problem in medicine (e.g. the form of aneurysms). For this reason, explainability should be documented, similar to a guideline, and workflows can be standardised (like unit tests). It is also important to establish and standardise tools for explainability (e.g. SHAP, LIME, saliency maps, graphical networks).

Explainable AI in Healthcare - Group B

Marc Lenz, Frank Broz, Norbert Jastroch, Andras Lorincz, Adriano Lucieri, Vivek Nallur, Carlos Peña, Francesca Pratesi

In the beginning of the workshop, the participants acknowledged that there is no objective measure of interpretability. This also poses a difficulty within the evaluation of explanations of an AI-system.
The criteria which define the quality of explanation are highly context dependent. Relevant factors here are for instance the user-role and the purpose of the explanation. A medical professional might have very different information needs than an AI-Developer or a layman. Thus, a good explanation does not only depend on the AI-System but also takes the information needs of the user into account. Another point which should be taken into account is the **domain of application**. For many domains, an extensive amount of **human knowledge** is already available. Ideally, an AI system should make usage of this knowledge and integrate it in its decisions but also explanations.
The participants also discussed why **explanations** are particularly important when it comes to AI systems in healthcare. Medical professionals are used to **blackbox systems** (i.e. drugs for which the underlying mechanism is not known. Explainability is often not very relevant for the end user. However, for AI-Systems in healthcare **interpretability** plays an important role in **building trust** of the user. Especially for decision support systems, **trustworthiness** is essential. If a user trusts the system entirely, they can be over dependent and run the risk not to detect mistakes and risks within the suggestions of the AI-system. If the user does not trust the system at all, it will not aid the decision at all. Therefore, the user should be enabled to understand the decisions of the system and decide when to trust a suggestion and when to decide differently.
An important point which was mentioned as well is that the e**xplainable model should ideally fit the cognitive model of the user**. It was argued that users would expect causal

relationships. **Causal relationships** which fit the cognitive model of the user are generally not inherent to AI-systems, therefore extracting those casualties from abstract models becomes an additional challenge. Furthermore, attention was raised to the factor of **interactivity**. It was argued that the user's understanding of the AI-system would be improved and they would be able to question the system's decisions in different ways. Examples that were mentioned include contrastive explanations, but also the usage of natural language, and conversational systems.

Overall, the participants identified a **gap between currently available explainability models and the human cognitive models**. One of the future challenges lying ahead is to develop methods and ways to close that gap. This will be essential for the development of trustworthy systems and accountability.

AI expertise in the Healthcare Sector

Emanuela Girardi, Andreea Avramescu, Alessandro Bregoli, Joscha Grüger

The healthcare sector nowadays faces several challenges in attracting talents and empowering their employees to provide AI-based solutions. Therefore the breakout session **" AI expertise in the Healthcare Sector"** aimed to address and to answer what the specific needs for AI training and upskilling programmes are and how these needs can be aligned with academic activities and doctoral programmes.

The participants of the breakout session started the discussion from the need to include a mandatory course of studies of AI in medical schools, but they all agreed that this is not enough and they o proposed to include a **computer science and AI course** in elementary, middle and high schools. This would create a good and solid base of AI, will make it easier for a University student of medical school to choose a course on AI for healthcare, and will provide all citizens with the necessary skills set to actively participate in the new AI society.

The healthcare sector faces several challenges in attracting talents and empowering their employees to provide AI-based solutions. What are the specific needs for AI training and upskilling programmes, and how can these needs be aligned with academic activities and doctoral programmes?

The proposal of the participants was to create a multi-disciplinary group, where the medical doctors, nurses, data and AI specialists participate in workshops on a regular basis to know and understand each other's problems (**Multi-disciplinary Workshop**).

However, not only doctors or nursing staff such as nurses but also AI researchers in the healthcare domain need to be trained on domain expertise such as healthcare ones and new jobs should be created in the hospitals for AI experts (**Train AI specialists in healthcare**).

A key point to be considered in AI & health is "**Trust**": trust is essential for physicians to use AI systems. Medical doctors are interested in understanding the reasoning behind the model. AI explicability becomes a key element in the adoption of AI by medical doctors.

In addition the group proposed the idea of a **European AI centre** that creates a network with University hospitals and is able to act quickly when there is a health crisis: during the pandemic, the local hospitals got in touch with local universities and research centres to

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develop solutions to tackle the COVID-19. Most of these solutions were developed locally using only the data collected locally at the hospital. If there had been an existing network of AI experts working on AI & healthcare, it would have probably been faster to give support to the medical doctors in tackling the pandemic.

HPC-AI convergence and the Healthcare Sector

Marco Aldinucci, Radovan Kavický, Elsa Kirchner, Aureli Soria-Frisch

The ability of artificial intelligence techniques to analyse data accurately is growing at a breakneck pace. Among these techniques, **Deep Learning (DL)** has benefited from crucial results in machine learning theory and the large availability of data to extract useful knowledge from them. The accuracy of this process is closely related to the quality and quantity of the data and the computing power needed to digest the data. Therefore **High-Performance Computing (HPC)** is an AI-enabling platform. On the other hand, supercomputers are shifting to GPUs due to their improved power efficiency and the need for increasingly GPU-enabled workloads, such as DL.
Healthcare is one of the critical sectors of the global economy, as any improvement in health systems impacts the well-being of society. European public health systems are generating **large datasets of biomedical data**, especially images that create an extensive database of untapped knowledge, as most of its value comes from expert interpretations. Nowadays, this process is still done manually in most cases. In the field of healthcare processes combining traditionally separate environments and HPC, Big Data analytics and Artificial Intelligence (AI) can overcome current problems and promote innovative solutions, in a clear path towards more efficient healthcare, for the benefit of people and the public budgets. High-Performance Computing (HPC) can propel AI applications toward grand challenges in healthcare: **genomics, drug design, and diagnostics.** Despite their potential, supercomputers are rarely used for AI. They are not yet equipped to effectively support specific AI software tools or securely acquire large amounts of data as medical applications require. Furthermore, artificial intelligence researchers are not used to the batch execution model of supercomputers.
Within this breakout session, there has been brainstorming on the open problems of **HPC-AI convergence**, such as programming and execution models, accuracy, reproducibility, portability. Based on these discussions, it was evident that High-Performance Computing is not yet perceived as an urgent need in the medical AI community, especially in Small and Mid-sized Enterprises (SMEs).
On the contrary, on-demand services offered by cloud services are **increasingly used in SMEs of the Healthcare Sector**. They are not having big/urgent enough problems, and cloud computing offers (from over-the-top providers) that come with practical (and easy to use) tools for exploiting AI solutions. HPC is, therefore, mainly used in the academic sphere. The discussions have also shown that multiple (modern) languages and interoperable data formats are needed for data analysis: Python toolboxes (TensorFlow, PyTorch …), Julia, etc..

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AI and bioinformatics: integrating learning and biomedical knowledge

Davide Bacciu, Ricardo Chavarriaga, Jan Komorowski, Tom Lenaerts, Lipps, Christoph Lipps, José M. Sempere, Carsten Ullrich

Developing learning models that are aware of and consistent with biomedical concepts and knowledge is a key research challenge to enable a widespread adoption of AI-based solutions in the life-sciences. Two key advantages have been identified throughout the discussion in the breakout session. First, learning-reasoning integration would **strengthen trust** of the life science community towards the use of data-driven methods and enhance self-explicability of the models, e.g. by having the model provide interpretations rooted on well-understood biomedical concepts. Second, learning-reasoning integration seems to be fundamental to surpass limitations of purely data-driven methods, such as machine learning and deep learning models, in **unfavourable conditions such as data scarcity**. In this respect, the breakout session has identified **rare diseases** as a relevant challenge which can highly benefit from an integrated approach capable of fusing symbolic knowledge, available under the form of knowledge graphs and interactomes, with high-dimensional/small-sample-size data. Rare diseases also require an integrative approach at the level of expert collaboration: **life science and AI communities need to unite efforts and a pan-European collaboration needs to be sought** and promoted. Rare disease patient associations can effectively support advocacy initiatives in this sense. The workgroup warmly advises to pursue and establish a **collaboration between the CLAIRE-TAILOR-VISION community and the ELIXIR initiative**, in particular as pertains to the machine learning focus group.

On a methodological level, the breakout session identified the research field of **learning from complex data structures** as a key enabler to effectively pursue the integration. On the one hand, **learning models for graphs** allow us to parse relational information in knowledge graphs and bio-networks, transforming such symbolic knowledge into numerical embeddings that can be effectively processed and incorporated by data-driven methods. At the same time, these models need to be extended to better **integrate the temporal dimension and temporal evolution of diseases**, to make them actionable and effective on biomedical data. Additionally, it is also advised to carefully investigate and consider the **role of bias in knowledge representation**, and how this can affect black-box systems that integrate such knowledge.

Input for the roadmap

Based on the results summarised in the previous section, the Organising Committee identified several topics which could be a valuable input to a European AI research and innovation roadmap. These topics will be presented to and further discussed with experts from TAILOR, VISION and CLAIRE in order to enrich the respective roadmap activities.

The below topics are the ones that stood out most prominently and will thus provide the 'core' of the input. However, when the roadmaps will be constructed, all inputs from the Theme Development Workshop will be considered.

Healthcare sector specific

- Ownership of Health Data needs (global/EU) privacy by design governance guidance for all involved multi-stakeholders based on the new data economy principles
- Availability of public data sets difficult due to patient data security
- Developing trustworthy AI tools is key to fight infodemics
- Legal question of data security and anonymity -> how to guarantee these when using federated learning? -> legal framework required
- Explainability is often not very relevant for the end user (i.e. patient, clinician, care professionals), as long as end user benefits from it
- Industrial stakeholders are not necessarily interested in creating better (more explainable) models and optimising the models
- Need advocacy on public healthcare systems and organisations to create funding opportunities and to support clinical data collection and sharing.

Not specific to the healthcare sector

- Trustworthy & Explainable AI are closely linked – more precise definitions needed for both
- AI competency courses in middle & high school to make it easier for students to take AI related courses at university – increasing the number of people with expert AI knowledge significantly
- Incentives for the participation in standards development needed (Especially for academics and SMEs)

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Summary and Conclusion

The high international interest that was expressed in response to the announcement of the "AI for Future Healthcare" Theme Development Workshop translated into excellent attendance of the event.

Sixty-seven participants joined the TDW, ranging from a diverse set of backgrounds. Fourteen (predominantly EU) countries were represented, with fourteen participants indicating that they are affiliated with industry, whilst fifty-one participants indicated that they are affiliated with academia (two participants indicated "other"). The participation of major industry representatives, with companies like Philips and NTT Data is particularly noteworthy and testifies to great interest on the part of industry. Equally important being the participation of those affiliated with the European Commission. The TDW, therefore, caught the attention of some of the most important actors in the field of Future Healthcare and brought together representatives from key companies, supra-national institutions, and academia. The workshop thus successfully provided a platform for discussions between representatives from academia, industry and politics: Discussions that are key in unlocking the full potential of AI in Europe.

The Organising Committee would like to express its deep gratitude to all experts for their valuable input and contributions to this Theme Development Workshop! Their active participation in the workshop and engagement in the breakout session discussions paved the way for the excellent results presented in this report.

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In addition to this list, 9 participants of the TDW preferred not to be mentioned publicly by name and affiliation.

The organisers would like to thank all participants for their valuable input and contributions to the Theme Development Workshop!

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