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Interdisciplinary research unlocking innovative solutions in healthcare

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ABSTRACT

Advances in Internet of Things (IoT) devices and in Machine Learning (ML) applications can provide valuable insights and predictions on personal health by optimizing data generation and processing.

Nevertheless, the flow of data about the health status of a patient brings a variety of technical, legal and economic challenges that need to be addressed through an interdisciplinary approach.

In this context, based on the action research methodology, the paper introduces an exemplary health-related activity recognition platform based on IoT, developed as a part of European-funded project Horizon 2020 in collaboration with academia and industry.

The platform proposes innovative solutions on how personal healthcare data can be processed and analysed, protecting users' privacy. The main strength of the platform is the interdisciplinary approach used within a triple-helix model, involving a variety of institutions, companies and researchers from different academic fields. In this perspective, the paper shows the potential that the integration of IoT and ML models have to offer and the main challenges that still need to be addressed.

Author contribution

DL worked on the paper design, theoretical framework, methodology and discussion.

KD, OT, HS, CP, YL, NC contributed equally to defining the findings, KD and OT also worked on revising the structure of the paper.

FS: was responsible of the research planning and coordination.

All Authors jointly defined the conclusions.

1. Introduction

Healthcare systems around the world are under pressure due to increasing demand for healthcare services and tight budgets for delivering them, especially as a result of aging and increasing chronic diseases (Van der Heide et al., 2015; Zhou et al., 2019). The COVID-19 crisis has increased this pressure even more (Cobianchi et al., 2020a; Biancone et al., 2021).

Digital transformation based on the integration of technologies such as the Internet of Things (IoT) and machine learning (ML) is recognized as a key component to address the above-mentioned challenges (Dang et al., 2019). On the one hand, IoT-based solutions can reduce the burden on healthcare systems by connecting medical devices and software applications to the healthcare IT systems and by remotely monitoring patients (Baker et al., 2017). On the other hand, ML techniques can provide useful insights and predictions on personal health through their learning capacity, and thus they may improve decision-making capabilities of both patients and healthcare providers (Farahani et al., 2020).

Advancements in IoT and ML have been found to be useful for addressing the COVID-19 crisis by detecting and monitoring cases (Otoom et al., 2020) and improving predictions on the spread of the virus (Abir et al., 2020). Nevertheless, the management of the COVID-19 emergency has made even clearer that applications need to be conceived and developed with privacy and security of users in mind (Qi et al., 2017; Pandey et al., 2020), which must be reflected when proposing solutions in the commercialization phase (Lo and Campos, 2018). Above all, COVID-19 has necessitated the application of interdisciplinary knowledge to manage resources, balance feedbacks, improve problem-solving and develop innovative solutions for the healthcare sector (Cobianchi et al., 2020b). A triple-helix model (THM) can help

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with this because it is based on the collaboration between institutions, academia and industry, which can provide access to deeper knowledge on how to design and apply innovative solutions (Leydesdorff and Etzkowitz, 1998; Ryan et al., 2018). However, ways to build an effective interdisciplinary THM are still needed, especially with respect to the healthcare sector. Thus, we aim to answer the following research question: "How can interdisciplinary research in a THM develop innovative solutions for the healthcare sector?"

To answer this RQ, the paper uses an action research methodology for the development and functioning of a prototype of health-related activity recognition platform based on IoT, named HEART, that aims at addressing the technical, legal and economic challenges faced in the digital transformation of the healthcare sector. The platform is the result of a THM collaboration founded by a European project – Horizon 2020 involving a multinational healthcare company (Philips), and two European universities: the University of Macerata (UniMC) in Italy, with experience in privacy and business aspects of data analytics and market trends; KU Leuven (KUL), in Belgium, expert in developing activity recognition algorithms and IoT.

The paper is structured as follows. In Section 2, IoT and ML developments and challenges are reviewed within the healthcare 4.0 era, underling the potential of interdisciplinary research and THM. Then in Section 3 and 4, the methodology and the HEART project are presented. In Section 5, the main solutions proposed by the platform are described while in Section 6, the role of interdisciplinarity is discussed. Finally, in Section 7, the theoretical, managerial and policy implications are highlighted.

2. Theoretical background

The healthcare industry has gone through various transformations from healthcare 1.0 to 4.0 as represented in Fig. 1.

While the healthcare 1.0 stage, identified between 1990 and 2007 (Sharma et al., 2019), allowed practitioners to record patient information on a computer in a doctor-centric approach (Hathaliya and Tanwar, 2020), the healthcare 2.0 phase (2007–2017) transformed the relationship between doctors and patients by giving access to more user-generated content. During this time frame, personal health records emerged, allowing patients to take control of their medical data (Randeree, 2009). Moreover, advances in IT and medical technologies were introduced (Tanwar, 2020), including first computational and data-processing systems. In 2017, the healthcare 3.0 phase (Sharma et al., 2019) was known to be delivering patients' electronic health records (EHR) (Tanwar, 2020), that is, patient data was compiled into a uniform repository from where authorized individuals could access it.

After 2017, the healthcare 4.0 era, which was based on more advanced technologies to be used for health management, started to emerge and is still going on (Drago et al., 2021; Massaro, 2021). It is based on the Industry 4.0 (I4.0) paradigm,[1] which is triggering a radical transition of traditional healthcare models towards e-health ones (Aceto et al., 2020). Amongst I4.0 enabling technologies, advances in the IoT are transforming healthcare systems from conventional to more personalized and predictable ones (Tanwar et al., 2020), enabling patients to be diagnosed, treated and supervised both physically and remotely in a more effective way (Qi et al., 2017).

The Internet of Medical Things (IoMT), also described as the healthcare IoT, is a combination of medical devices and software applications offering broad healthcare services, which are connected to the healthcare IT systems. The IoT can extend the boundaries of healthcare outside of the hospital settings by transforming the hospital-centric ecosystem to the patient-centric one (Farahani et al., 2020).

[1] The industry 4.0 paradigm is a complex and connected technological system that emphasizes the opportunities of integrating all elements in a value-adding system (Neugebauer et al., 2016).

The data collected by IoT facilitates self-management of health by monitoring patients remotely (Woo et al., 2018), for instance by helping doctors and patients keep track of personal health data related to daily activities, including exercises, vital signals, disease symptoms and nutrition. The collection of this data can empower patients to understand and manage their health-related activities (Shin et al., 2019). In addition, IoT-based solutions are expected to enhance the quality of care and reduce healthcare costs (Nguyen et al., 2017; Chiuchisan et al., 2014) and overcome the problem of repeated examinations and misdiagnoses by facilitating sharing, analysis and retrieval of patient's health information in a timely manner (Chandy, 2019).

To provide the above-mentioned benefits, the huge data collected, referred to as Big Data, needs to be stored and analysed (Sousa et al., 2019). To this aim, IoT technologies need to be integrated with artificial intelligence (AI), particularly ML, applications. Precisely, ML is a subset of AI, defined as a branch of computation algorithms that emulate human intelligence through experiential learning from the environment (El Naqa and Murphy, 2015). Based on their learning capabilities, ML solutions have enabled IoT platforms to make accurate predictions in the healthcare sector (Helm et al., 2020; Tahsien et al., 2020), monitor health-related data anywhere at any time and provide real-time insights (Farahani et al., 2020). The following sub-section will explain IoT and ML solutions in the healthcare sector in more detail, outlining the challenges that must be addressed for their widespread adoption.

2.1. IoT and ML developments in the healthcare sector

Amongst the applications of IoT in the healthcare sector, a great focus has been placed on IoT-wearables, described as smart devices connected to the internet, which can be worn to gather, send out and receive data to take smart decisions (Dian et al., 2020). Wearable devices attached to the patient can provide valuable information to healthcare professionals during the process of treatment or therapy (Kos and Umek, 2019), assisting patients with self-diagnosis and behaviour adjustment intervention (Piwek et al., 2016). IoT wearables and mobile devices based on positive computing systems can also address the matters of health and well-being, such as stress and depression (Lee et al., 2019). Furthermore, current IoT devices are being designed to be integrated with healthcare coaching programmes to support the patients and their families for following treatment coaching programmes (Amato and Coronato, 2017).

By using ML models, it is possible to gain real-time insights and predictions that improve the decision-making capability of both patients and healthcare providers (Farahani et al., 2020).

The applications of ML solutions in the healthcare sector are diverse. They are being increasingly used for risk stratification in the case of specific infections, identification of specific risk factors to overall risk, and prediction of the emergence and spread of diseases (Wiens and Shenoy, 2018).

ML methods are becoming also particularly important in the management of chronic disease based on the fact that many chronic diseases are composed of patients with similar but distinct underlying disease mechanisms. For the diagnosis and forecasting of these diseases, predictive models, such us support vector machines (SVM), logistic regression (LR), clustering, are used (Battineni et al., 2020).

Healthcare domain is often characterized by abundant unstructured and missing data; hence, advances in ML applications are proposed to deal with these issues. Typical unstructured data includes medical video data, physician's notes in HER and patients' feedbacks. Instead, missing data can be due to faulty data collection and transmission methods. For example, in the case of wearables, the sensors may detach from the skin, lose connection or run out of batteries. For dealing with unstructured and free text data that is without any constraint of format, natural language processing (NLP), built on algorithms for understanding human language, is the main solution proposed to handle natural language for computation (Balyan et al., 2019). Instead, missing data or incomplete

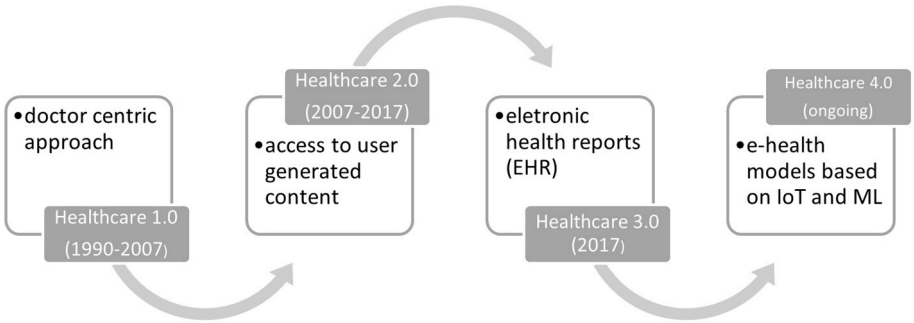

Fig. 1. Healthcare transformations.
Source: Authors' elaboration based on timeline of Sharma et al. (2019).

data collection can be dealt with built-in capabilities, such as decision trees with surrogate splits, pattern sub-models, or incorporation of autoencoders (Nijman et al., 2021).

Despite the fact that IoT and ML solutions can solve many problems in the healthcare sector, a variety of challenges in technical, legal and economic domains are still limiting their adoption (Brous et al.., 2020; Farahani et al., 2018). They are discussed below.

From a technical point of view, the technical heterogeneity of IoT devices makes their architecture design challenging in terms of interoperability and integration (Selvaraj and Sundaravaradhan, 2020). Manufacturers, providers and end users are still seeking standards for the operability of IoT solutions. However, standardization is complex since IoT involves a variety of disciplines that are regulated differently, and for IoMT, the complexity increases due to the specific medical standards (Farahani et al., 2018).

IoT devices can also pose a threat to users' security and privacy, and privacy concerns increase when the patient's information is shared amongst multiple applications (Zeadally et al., 2019). Data leaks in IoT devices could impact individual privacy by revealing sensitive personal information, such as personal behaviours or financial information (Skarmeta et al., 2014). Security and privacy need to be taken care of throughout the lifecycle of IoT devices – from specification to deployment.

The above-mentioned challenges that are restraining IoT deployment must be integrated with ML complexities. ML algorithms use data that is subject to privacy protections, requiring developers to pay attention to ethical and regulatory restrictions at each stage of data processing. In this field, the European General Data Protection Regulation (GDPR[2]) has established several rights that must be respected by those processing their data. The GDPR requires any health data, collected and monitored – including biometric and genetic data – to comply with strict regulatory guidelines, and this extends to the physical premises where healthcare information is stored and managed by healthcare organizations. This means that data used to train algorithms must have the necessary authorizations for use. However, determining the specific data uses will depend on data type, jurisdiction and purpose of use.

To gain trust of patients and increase adoption rates by providers, ML must be compliant with data protection requirements and regulations. Addressing these ethical and regulatory issues is essential for avoiding unnecessary risks that will hinder the further progress of ML (Vayena et al., 2018). Moreover, the development of IoT solutions must be monitored and evaluated also from an environmental point of view to limit the presence of dangerous impacts and safeguard the smart utilization of resources (Nižetić et al., 2020).

Last but not least, the high implementation costs may add further pressure to the tight budgets of the healthcare sector (Brous et al., 2020). This is why the commercialization of the solutions based on sustainable business models must be considered from a company's perspective (Lo and Campos, 2018) for addressing barriers and challenges of their adoption (Oderanti et al., 2021).

2.2. Call for interdisciplinary and collaborative approaches

In order to push the adoption of IoMT, the range of challenges mentioned above must be tackled, leveraging a holistic multi-layer approach (Farahani et al., 2018; Maghsoudi et al., 2020).

I4.0 technologies for their intrinsic characteristics are prompting collaboration by enhancing both internal and external relationships (Nasiri et al., 2020). Reka and Dragicevic (2018) pointed out that stakeholders with different backgrounds need to communicate to explore the next generation of IoT technology and handle its complexity. However, Jia et al. (2019), after recognizing the increasing interests in interdisciplinary research on IoT, underline that the IoT sector suffers from a top-down approach and users are not yet the core drivers of the change. To apply IoT, companies need to embrace interdisciplinary education in the areas of law, economics and engineering and participate in planning and developing educational programs in cooperation with educational institutions. By doing so, they would be also involved in designing the skills that will be tailored to their IoT needs (Kiel et al., 2017).

This means that the call for sustainability and high-quality solutions in IoT can be addressed with a cross-sectoral, multidisciplinary, and interdisciplinary perspective, focusing on innovation, information and collaboration between different stakeholders (Pereno and Eriksoon, 2020; Bardhan et al., 2020; Massaro, 2021).

In particular, collaboration amongst universities and industries provides access to a greater knowledge for research compared to wholly in-house development (Numprasertchai and Igel, 2005).

The university–industry collaboration frequently allows industrial partners to supervise and obtain knowledge about technological advances directly by universities. However, in order to deliver digital applications with positive effects on end-users, it is necessary to have a common understanding of the objectives of such collaborations (Austin et al., 2021). University-industry collaborations can unlock open innovation (OI) approaches by transferring knowledge outside the organizational borders (Chesbrough and Crowther, 2006) and, in turn, tackle existing challenges of healthcare ecosystems (Secundo et al., 2019). These collaborative approaches can be boosted within a THM that is used to foster regional economic growth and promote entrepreneurship through understanding the dynamics of interactions between the three institutional spheres of university, industry and government (Etzkowitz et al., 2007). The interaction between these three helices can differ in terms of strength and dependencies (Etzkowitz and Leydesdorff, 2000). The global tendency is towards a balanced model for a more flexible,

[2] Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation).

overlapping system, with interchangeable roles (Etzkowitz, 2002). Nevertheless, to be successful, these models require careful planning and strong commitment from participants of the THM (Hyrkäs et al., 2020). Challenges often occur in defining the problem and achieving a joint view on potential solutions (Wassrin et al., 2015).

As the first step, the actors' motivations and the processes used for transferring knowledge should be well understood to decide how to unlock OI models (Secundo et al., 2019). In this direction, OI can become a policy instrument in the healthcare industry and improve the knowledge transfer amongst stakeholders through demand-driven models (Pikkarainen et al., 2020).

Within the context of increasing demand for personal healthcare based on IoT and ML applications, we intend to explore the role of an interdisciplinary approach in developing and bringing to the market innovative solutions that comply with technical, legal and economic requirements.

3. Methodology

By following an action research (AR) methodology (Robertson, 2000; Greenwood and Levin, 1998), this study describes the development of the prototype of a health-related activity recognition platform based on IoT, named HEART. This platform was designed to be introduced in Europe and then extended to the Chinese market.

The development of HEART provides an interesting example of how interdisciplinary research within a THM can prompt the development of innovative and sustainable solutions, answering to the challenges faced by the healthcare sector. In fact, the platform, funded under the Horizon 2020 program of the European Commission, within the Marie Sklodowska Curie Actions – Industrial Training Network, was developed leveraging on the involvement of industry and universities with different background (economics, law and engineering). Specifically, the THM was used in the project development as a guiding heuristic through which universities played a more active role in innovation by driving and coordinating the activities with institutions and industry (Cai and Etzkowitz, 2020).

As any AR, the development of HEART prototype was based on a 'systematic and orientated around analysis of data whose answers require the gathering and analysis of data and the generation of interpretations directly tested in the field of action' (Greenwood and Levin, 1998, p.122). Precisely, the HEART project followed a spiral process between action (i.e. change and improvement) and research (i.e. understanding, knowledge) (Dick, 2001). This spiral process (see Fig. 2) was translated in the definition of the already academically acquired knowledge, the knowledge gaps and research hypotheses and firms' perspectives on the matter (*conceptualisation*). This 'conceptualisation' stage considered the research correlations amongst the different backgrounds (e.g. engineering, law and economics). Then, the core research phases were carried out, including the collection of data, their analysis, results formulation and validation *(data collection and consultation)* followed by the development of the HEART prototype (*development*). Finally, sustainable and effective innovation priorities were identified, and strategies were formulated for enacting their implementation in Europe and China (*customisation*).

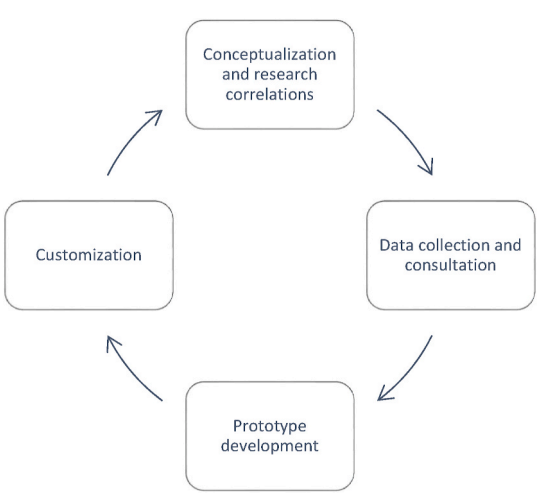

Fig. 2. Action research model of HEART.

The key data sources derived from the AR and used in the discussion are based on the project proposal, scientific deliverables (n.11) and use cases (n.3), which are integrated with final feedbacks collected from project partners. Furthermore, six of the authors of the paper are researchers who were directly involved in the prototype development.

As underlined by the doctrine, the AR perspective can be beneficial for research in the healthcare domain, as it supports collaboration between researchers and practitioners (Tanna, 2005). Moreover, researchers may find the AR technique of value when studying innovative ways of engaging in collaborative and interdisciplinary work to improve patient care (Tanna, 2005).

Indeed, contrary from other research methods, action researchers do not merely observe something happening, but they work to make it happen (Gummerson, 2000). The direct participation of the AR enhances knowledge acquisition and specifically practical knowledge while contributing to theory development (Reason and Bradbury, 2001).

4. The HEART platform – the result of a THM interdisciplinary collaboration

The HEART project started in 2017 as an industrial training network program, with the aim of training young researchers and integrating socio-economic sciences and humanities (SSH) perspectives in an innovative way, with technical skills, creativity and entrepreneurial allure. The research team members included four engineers, one legal expert and one international business expert.

The consortium working on the project was composed of a large healthcare multinational company (Philips) and two European universities: UniMc, in Italy and KUL, in Belgium. Philips is a global firm developing healthcare projects along the care continuum. KUL has extensive experience in the development of activity recognition algorithms and IoT technology. UniMc has strong experience with privacy and business aspects of data analytics as well as in global market trends, with a focus on China.

Partner institutions included six prestigious organizations: Fudan University in China (with expertise in IoT developments in healthcare), Philips Research China (as R&D center of Philips in China), University of Chinese Academy of Sciences (with expertise in international business and consumer analysis for the Chinese market), Jacobs University (with expertise in international business and information systems, in Germany), Isinnova (in Italy with extensive experience in interdisciplinary research approaches) and Eurocentro (in Italy, with project management know-how). Furthermore, external stakeholders were part of

collaborative network: Active Assisted Living (AAL) programme,[3] The Alliance for Internet of Things Innovation (AIOTI)[4] and Exprivia China.[5]

Since the beginning of the project definition, the partners identified four main challenges that the HEART platform had to address:

- *Data analytics for personal-health coaching.* From wearable and mobile devices, large streams of data can be acquired that have to be translated into actionable insights for the management of personal lifestyles.
- *Data processing for personal health coaching.* A large amount of data also needs to fulfil the necessary requirements of data processing. In many applications, raw data is not needed and derived data can also determine the state of a person.
- *Protection of private and personal information.* Activity recognition and monitoring vital signs are highly sensitive to privacy issues. Solutions should protect users' privacy and comply with privacy laws from the conception of products and services to their commercialization.
- *Consumer perspective and market penetration.* While IoT is a growth area for the EU Member States, a key challenge for EU companies is the exploitation of their innovation potential abroad. A huge market is composed of the Chinese consumers, but solutions have to be tailored to the needs, behaviours and habits of this specific context.

The partners not only exchanged their specialized knowledge during this project but also provided the physical infrastructure for the development of HEART. Philips infrastructures included in-house developed software environments to handle and pre-process activity for data streams: Philips consumer-grade health watches with a built-in accelerometer and PPG sensors; ambient light sensor; software infrastructure platform to collect the health watch sensor data for large groups of people and experience lab equipped with a home environment, ideal to collect data for the detection home activities. Regular interaction between the research team and the staff was ensured within the Philips Business unit, giving guidance on entrepreneurship and intellectual propriety. KUL infrastructures included a wireless shimmer set and data acquisition systems for audio and video to perform measurements in the field; a living lab to carry out monitoring experiments on persons simulating activities in a realistic environment; an electronic lab that enabled the development of electronic circuits and a number of crunchers to perform big data analytics. The researchers also took advantage of the middleware platform for remote programmability and the frameworks that enabled the developers to integrate privacy and security requirements from the beginning of the development process (privacy-by-design, security-by-design). At UniMC, the researchers were located at the China Center for conducting research on issues related to China regarding economics, law, politics and international business issues.

In this context, the six researchers were called to integrate novel algorithms and solutions into one health integrated activity recognition platform to be able to detect activities from heterogeneous data, using scalable algorithms, while safeguarding the user privacy and embedding the needs/habits and perspective of the consumer. The prototype had to be designed to be as compatible as possible, with an already existing platform for healthcare solutions, i.e. the Philips Health Suite Digital Platform (HSDP). In the process of integration, it was important to ensure maximal uptake of the work into Philips products and services. The Philips HSDP[6] is grounded on reliable device-connectivity services on a global scale.

To reach these objectives, the HEART activity recognition platform was built around the following four layers:

1. *Data collection layer*: The software and hardware components concerned with measuring the raw data.
2. *Data pre-processing layer*: This layer ensures that the collected data typically undergoes transformation (i) to prepare the data for the analytics services and (ii) to take security and privacy measures in line with the requirements entailed by legal policies and application specific needs.
3. *Data analytics layer*: The data analytics layer is one of the core layers of the HEART platform. It concerns with extracting useful information from the data by using state-of-the-art and novel data analytics and machine learning techniques.
4. *Application layer*: This layer contains the actual personal health applications that are supported by the HEART platform.

To define the layers, six researchers were trained on the topics related to their individual research projects through local seminars or courses as well as internal training project meetings organized by beneficiaries and partner organizations. Specific training was devoted to interdisciplinary research skills to strengthen their capacity to conduct research according to a holistic approach, communicate their results to scientific communities of other disciplines, conduct the individual research project and integrate specific knowledge with results coming from other projects involved in the HEART project.

5. The innovative solutions proposed by the HEART platform

The solutions proposed by the platform aimed at ensuring *data availability* in the processing stage. Indeed, ML requires large and high-quality datasets to train models that can generate accurate predictions or classifications on personal healthcare. Nevertheless, the availability of such datasets is scarce. The HEART platform addresses two major aspects of this problem, when labelled data is limited and no other data is available, and when unlabelled data is available but labelling budget is not. Such issues are faced with data augmentation methods applied in the data pre-processing layer along with training and validation of deep neural network-based on NLP. A second technical aspect dealt by the platform is linked to the *personalization of ML models.* Health data generated from various e-health applications are often time-series-based, meaning that a certain parameter is studied over time and predicted for a future time. These applications can be personalized for individual users such that the recommendations can be tailored. However, the personalization of ML is based on the availability of training data from individuals. In this case, the platform – by using regression models – proposes a methodology to train models of time-series datasets with missing or sporadic data.

In defining these solutions, the team of engineers had to collaborate with the legal experts to make sure that a set of requirements were considered when designing the platform. As a result of this collaboration, a threat and risk management (TRM) framework was introduced to comply with security and privacy issues. Then, in collaboration with economic experts and Philips, a *business model* for the HEART platform was designed, considering the European and Chinese markets. The

[3] Active Assisted Living (AAL) Programme is a European programme funding innovation. It supports the development of products and services for those facing some of the challenges of ageing and for those who care for older people who need help (see: http://www.aal-europe.eu).

[4] AIOTI was initiated in 2016 to contribute to the creation of a dynamic European IoT ecosystem and sped up the take up of IoT. Members include key European IoT players (large companies, successful SMEs and dynamic start-ups) as well as research centres, universities, associations and end-user representatives (see: https://aioti.eu).

[5] It is the Chinese subsidiary of Exprivia, a market leader in process consultancy, technology services and information technology solutions, which also serves the healthcare industry (see: http://www.exprivia.com).

[6] Philips HSDP is a native cloud-based infrastructure and a set of core services needed to develop and run connected healthcare applications; it is open to third parties.

consumers' perspective (demand side) on the use of digital healthcare was considered necessary to design a marketing strategy and business models (supply side) for the HEART platform.

In the following paragraphs the two technical solutions with their use cases (5.1 and 5.2), the TRM framework (5.3) and the business model (5.4) are discussed.

5.1. NLP models for dealing with unstructured data

The HEART platform relies on both objective and subjective data on health-related behaviour, including aspects such as satisfaction and emotions. Subjective information can be retrieved using unstructured textual inputs from the user via direct typing or translated from their voice.

The advantages of using free-text inputs from users are two-fold. First, it is user-centred and therefore users feel free to describe their behaviour. Secondly, these user-generated inputs contain rich user-specific information that can be employed for personalized healthcare services.

Nevertheless, there are some challenges in analysing free-text for health-related behaviour analytics. Indeed, free text is unstructured, noisy, and ambiguous. This makes it difficult to do manual programming or feature engineering.

ML approaches based on NLP can address this issue, because ML models can learn from training data. To train a ML model, however, large-scale training data is required, because the performance of the model is strongly related to the size of the training data. Furthermore, it must be considered that not only data acquisition is difficult but also data labelling is labour-expensive, especially in the healthcare sector. To solve these two challenges, the free-text analytics component in the HEART platform consists of two following parts:

- A deep neural network (DNN)-based NLP model to process free-text inputs from users and classify them into multiple categories
- Data-efficient learning strategies

On the one hand, a data augment technique was proposed to increase the initial training data. On the other hand, a semi-supervised learning was adopted to train models iteratively to minimise the manual data-labelling process by utilising the trained model for labelling.

To validate the model, text data was collected via a web-based survey. Participants of the study were asked to complete a sleep-related questionnaire in free-text sentences and select sentences that represented their answers. In the specific use case, the free-text responses were used as input for the classification model and outputs were one or more class labels to perform multi-label classification. The study collected 16096 sentences; 90% of the collected data were used as the training set to train a model and the remaining 10% were used as the test set to validate the performance of the model. The experimental results showed that data augmentation can contribute to the improvement of performance, especially when the size of the labelled training set is small. Also, semi-supervised learning with pseudo-labels can enhance performance (Shim et al., 2020).

Another data-efficient learning strategy is proposed to not only reduce manual labelling efforts effectively but also maximise the utility of data (Shim et al., 2021). The proposed learning strategy consist of three elements: (i) task-specific pre-training to exploit unlabelled task-specific corpus data, (ii) label augmentation to maximise the utility of labelled data and (iii) active learning to label data strategically. The proposed method was validated in the aspect-based sentiment analysis tasks with custom dataset collected via a web-based survey on sleep-related topics and the benchmark the dataset. During the experiments, each dataset was divided into train, validation and test set to conduct five-fold cross-validation, and the averaged results have been used for report. Experimental results show that the proposed label-efficient training scheme can reduce manual labelling efforts by 2–3 times and can contribute to better generalisability with both datasets.

5.2. ML for tailored predictions and recommendations

ML models can be personalized for individual users to provide tailored predictions and recommendations. By using personalized ML models, the platform would be able to intervene in a timely manner, enabling the detection of the disease as early as possible. The personalization of ML is based on lots of uniform training data. Nevertheless, data collected in a real-world setting, especially in the healthcare sector, is sporadic. Data is often plagued by missing data, which is non-uniformly sampled in time. Therefore, to provide timely insights, ML models should adapt actively to the personal data by using only a few time-series observations, without requiring lots of training data from the individual. With enough individual measurements across time for training ML algorithms, it is possible to build accurate models of individuals' health status. Thus, a framework for time-series prediction was defined to enhance health prediction capabilities.

Fig. 3 shows training data coming from 'M' pre-existing users that collect time-series signals from 'N' heterogeneous sensors across different modalities. These M users are used to learn a model such as a regressor or a classifier that represents a general population model. The parameters are then optimized for personalising the model for test user by tweaking the general model with the local model learned from limited test user data.

The proposed approach was tested on data collected from pregnant women. Studies suggest that only 30% of pregnant women end up being adequately weighed at their full term as recommended by the Institute of Medicine recommended guidelines. Several risks have been associated with inappropriate weight for the mother and the infant. Hence, early recognition of signs of weight gain during pregnancy is necessary (Hutcheon et al., 2018).

Data were collected from pregnant women in the Netherlands in Europe and in Shanghai, China. Women who were in their gestational week 5 or later were recruited randomly from midwife practices in Europe and in China. A digital weighing scale was connected via a mobile application to the server to collect data for processing and predicting the end-of-pregnancy weight gain (Puri et al., 2019; Puri et al., 2021).

The individual weight gain measurements during the pregnancy are modelled using a polynomial-based regression, where the input is weight measurements from individual subjects across the duration of their pregnancy. Since using only individual weight measurements is not sufficient for accurate estimation of end-of-pregnancy weight gain, the models from the users in the training set who had underwent pregnancy are aggregated as shown in Fig. 4. Precisely, the predictions were performed by learning a general ML model from the population training data and then tuning the general model to a personal one by readjusting the model parameters based on limited individual measurements.

To test the approach's efficacy, a 'leave one subject out' method was experimented for cross-validation, where one subject was treated as test subject and the model was trained on the rest of the subjects. This procedure was adopted till all subjects were treated once as test subjects. The final prediction was the weight gain at the end-of-pregnancy. The efficacy of the system was measured by averaging the error obtained in estimating the weight gain of all the subjects from two different geographical regions (Europe and China).[7] Other state-of-the-art

[7] 2.45 kg and 2.82 kg in forecasting end-of-pregnancy weight gain on European and Chinese populations respectively, whereas the best of state-of-the-art yields 8.17 and 6.60 kg on respective populations while utilising only 140 days' worth of pregnancy data.

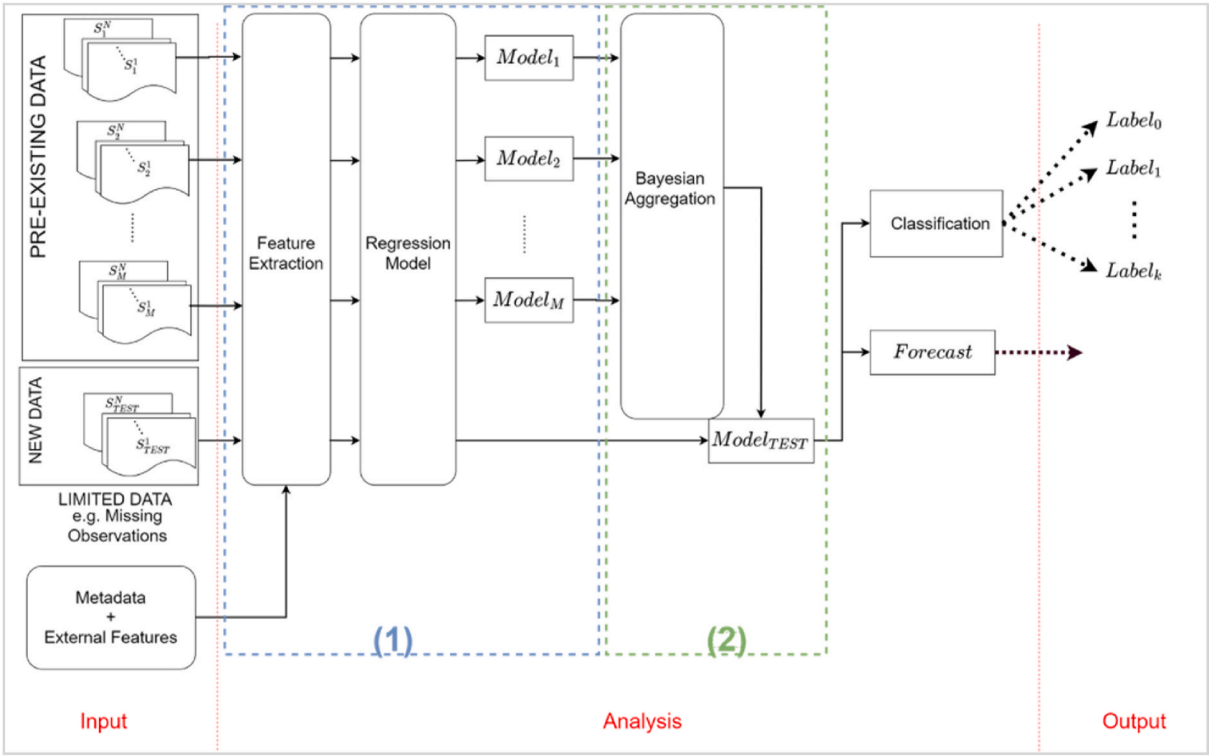

Fig. 3. Pipeline flow of learning from limited data with heterogeneous data sources.

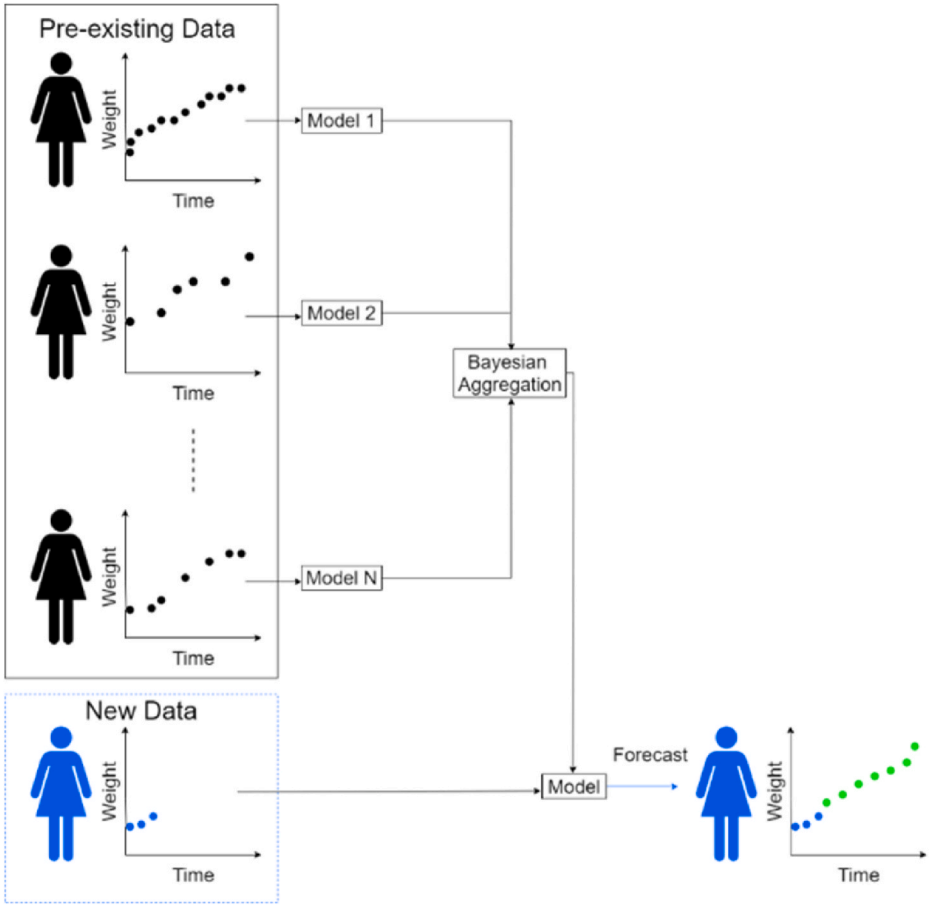

Fig. 4. Application of the proposed pipeline for gestational weight-gain prediction.

methods[8] were tested, and the results confirmed that the proposed approach outperforms them, especially when early prediction in such a scenario, is of utmost importance (Puri et al., 2021).

Nevertheless, in proposing these technical solutions, the group of engineers had to deal with the fact that the personalization of ML applications involves the collection of sensitive and personal user data, which can risk the violation of user privacy. To overcome this issue, the platform takes an orthogonal approach by addressing the challenges arising from the user's side. Therefore, the platform develops ML applications in a manner that the personal data remains on the user devices and only the ML model or updates are stored on the cloud. This leads to the minimization of shared data and limitation over the collected and stored data by the application provider. Thus, the data pre-processing layer is offloaded towards the mobile devices, away from the centralized server, while the data analytics layer is shared between the device and the server. In this way, training costs are minimized and user privacy can be preserved.

Moreover, by using the logic of personalized ML, the platform can also provide a tailored recommender system that facilitates decision-making amongst users by enabling them to view content from the vast repository of information from the internet and by providing them with personalized recommendations. However, these recommender systems are based on a plethora of personal information collected from the users to improve their performance. This leads to a trade-off between the personalization of recommender systems and the protection of the privacy of its users. To build the recommendation system, a matrix factorisation method is used. The matrix factorisation is employed to comprehend the underlying characteristics of user ratings for articles by expressing the user-article rating matrix into two lower-ranked matrices called affinity matrices. These affinity matrices implicitly express the characteristics of users and articles, and thus include personal information. The matrix factorisation method is employed since the data collected from the users is quite simple, i.e. the number of times when users interact with an article and whether they like an article. Thus, matrix factorisation facilitates extraction of useful information from the ratings.

This means that sharing this information with a cloud server can lead to privacy implications under the lens of the GDPR. Google proposed the federated learning paradigm to tackle such problems and to enable privacy-preserving learning relying on (i) training models on device by using locally stored data, (ii) transmission of ephemeral updates to the central server and (iii) aggregation of these updates to train a central model. Within the HEART platform, the application of the federated learning paradigm to recommender systems and, in particular, matrix factorisation was used to understand the extent to which the user data sharing can be minimized while maintaining high levels of accuracy and optimization on-device training can affect the performance of the system (Dolui et al., 2019).

5.3. TRM framework for satisfying privacy requirements and meeting risk budgets

As mentioned, every e-health IoT system has security and privacy requirements, and the variety of requirements continues to increase. The regulations establish core principles to which compliance must be attained and demonstrated, and thus shape the key requirements that have to be met.

Implementing privacy and security principles and requirements is non-trivial and demands not only the awareness about them but also the extensive expertise on how an architecture of a compliant system should look like. Nevertheless, even if a system satisfies regulation-driven requirements, it is not free from security and privacy risks. Every use case inherently possesses a certain 'risk appetite', and thus risk budget, but those can be met only in case of deep understanding of the possible threats and risks.

The TRM framework is introduced for the HEART platform for meeting risk budgets and satisfying privacy requirements through the assessment of every architectural variant and by performing metrics-based scoring as well as validation on meeting identified requirements. The framework consists of four stages that are depicted in Fig. 5.

The first stage of the framework covers the modelling of the space of all possible features that the system architecture may possess. This can be reached via performing feature-oriented domain analysis and creating a corresponding feature model. Such a model enables the creation of data flow diagrams (DFDs) of every architectural variant and establishes opportunities for their further assessment.

The second stage of the framework is responsible for the assessment itself. It can be reached based on the input of the first stage, which is a set of DFDs that corresponds to every architectural variant, through applying STRIDE[9] and LINDDUN[10] threat assessment methodologies. These methodologies provide systematic support for the elicitation and mitigation of privacy threats and, in its essence, contain activities for modelling the system. The output of threat assessment within this stage is also used for advanced risk assessment that is based on FAIR[11] ontology.

As a result of this stage, a set of threats and risks per each

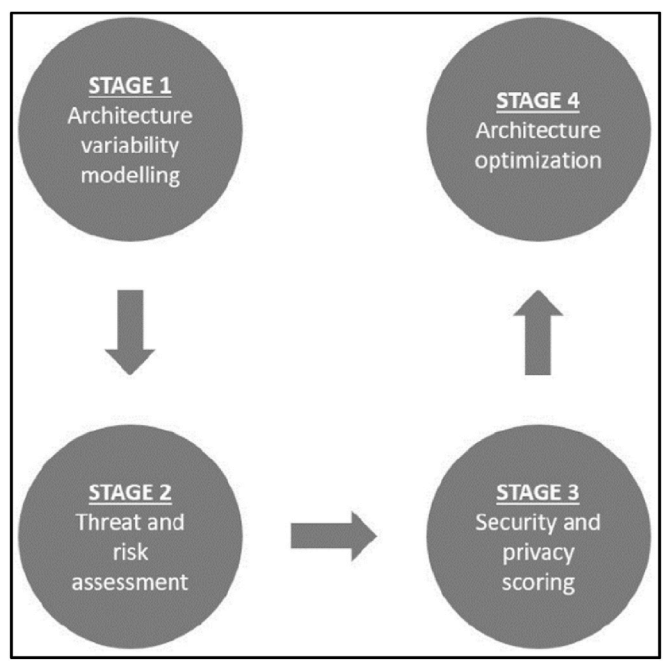

Fig. 5. Stages of the TRM framework.
Tomashchuk et al., 2019

[8] Long short-term memory networks (LSTM) (Hochreiter and Schmidhuber, 1997); auto-regressive integrated moving average; ARIMA (Box et al., 2015).

[9] The STRIDE model was developed by Microsoft in order to help security engineers understand and classify all possible threats on a server. The name of this model is an acronym for the six threats: Spoofing; Tampering; Repudiation; Information disclosure; Denial of service and Escalation of privileges.

[10] LINDDUN is a privacy threat modelling methodology that supports analysts in systematically eliciting and mitigating privacy threats in software architectures.

[11] Factor Analysis of Information Risk (FAIR) is the only international standard Value at Risk (VaR) model for cyber security and operational risk. The FAIR model is broken down into an ontology to demonstrate how key elements constitute risk to an organization.

architectural variant is obtained.

The third stage builds on the input of the previous stage and establishes scoring for architectural variants based on risks that have been obtained during the assessment. This scoring may rely on multiple metrics that are relevant for a particular platform as in the case of HEART. For example, metrics focused on de-identification and the way of optimizing outcomes of such a process have been covered by previous work (Tomashchuk, 2019). The scoring within this stage enables selecting the most appropriate system configuration or a set of configurations based on their corresponding risks.

The last stage of the framework is responsible for the verification on meeting the privacy and security requirements by the architectural variants that satisfied the risk budgets. This can be done by checking DFDs on the presence of components that are specified by the requirements of the GDPR and the Cybersecurity Law (Tomashchuk et al., 2019).

Altogether, the TRM framework enables improvement of security and privacy for e-health IoT platforms by employing and extending STRIDE and LINDDUN methodologies. Furthermore, it also allows developers and architects to select from a broad variety an appropriate configuration of the system that, in turn, satisfy given requirements and risk budgets.

5.4. The business model of the HEART platform

The technical and legal side was integrated with the business and marketing perspectives of the platform. The HEART Platform is recognized as a service-based business model focused on health management and connected data services. The core value of the HEART platform focuses on addressing the challenges posed by the growing amount of data generated from connected devices by optimizing data processing time and costs for healthcare service providers and users. With specific reference to the European and Chinese market, the platform addresses the lack of systematic professional health coaching and lifestyle coaching services and the lack of solutions for specific chronic health issues, such as pregnancy women weight control, sleep quality for users, as the use cases presented, as well as predicting Alzheimer's disease cognitive.

Since the HEART platform is created by a European corporation in and for the Chinese market also, a comparative analysis of the legal regimes on data protection existing in Europe and China was an indispensable requirement for the future implementation of the platform. In particular, a contextual data processing-based approach was developed to facilitate the minimum data collection and processing principle stressed by the GDPR. Therefore, the legal experts employed legal–historical analysis to explain the factors at macro-level (e.g. political culture, laws and regulations concerning the market, pros and cons of enforcement) and micro-level (e.g. data protection laws and norms) that constitute the data regulation. Thanks to their insights, the platform is able to connect the healthcare service providers and the healthcare systems in Europe and China by performing edge computing and privacy protection services. Edge computing in combination with privacy protection data processing services can reduce processing time and costs by saving cloud service fees and security problems. Considering the differences in data-collection protocols and standards, the HEART platform develops an open IoT architecture to process data and faces technical problems of incompatibility between healthcare service software providers and hardware providers. The platform creates a data processing API to process the growing amount of data generated for personal care purposes for government, tech companies and hospitals.

Built on these premises, the major profits from the HEART business model are expected from cooperation with hospitals, tech companies and governments from China and Europe. The platform specifically aims to provide insights for hospitals to help patients to deal with chronic diseases (B2B model) for individuals to manage health conditions (B2C model) and governments for effective health management and policy making (B2G model).

With particular reference to China, the marketing strategy was defined through institutional stakeholder interviews and consumer focus group studies that were conducted in China in 2019. Interviews with government officials ($n = 2$), business managers from tech companies ($n = 6$), doctors ($n = 2$), and focus groups study with individual users ($n = 64$) were conducted. For the focus group, four discussion groups were formed to discuss the topic of access to healthcare, healthy living, elderly care, and chronic disease management. Each group consisted of sixteen members: eight from urban Beijing and eight from rural Beijing. The stakeholder interview followed the interactive learning and action (ILA) approach to understand how to implement telehealth solutions in China, based on the steps of exploration, consultation and integration. Given the income distribution variabilities in different cities, the collected results showed that HEART is particularly suitable for the user group with high household income, private insurance coverage and better health understanding of smart health solutions (Chen et al., 2021).

6. Discussion – the value of interdisciplinary research in the healthcare sector

The HEART platform was designed by exploiting the relationships and complementarities between the company and the two universities involved, on one hand, and the interdisciplinary background of the researchers on the other.

In setting the HEART project for the European call under Horizon 2020, Philips, UniMC and KUL were able to carefully define the problem (i.e. how to use IoT tools and sensors to develop healthcare solutions for a better quality of life), build a common vision and plan all the activities to be carried out in a four years' time frame (Hyrkäs et al., 2020; Wassrin et al., 2015). The starting phases of planning were essential to build a strong commitment towards the project. Since the beginning, the partners established how to unlock OI models for designing the HEART platform. In this sense, all phases of implementations (including training and co-creation activities) were defined to transfer knowledge amongst the researchers involved (Secundo et al., 2019).

The exchange of knowledge represented the key asset of the HEART platform. In particular, the exchange of interdisciplinary knowledge was embedded in all activities of the project, leveraging the different expertise of the partners. Researchers were trained and involved directly in designing the HEART platform, focusing jointly on technical, legal and economic aspects. Many training sessions were dedicated to providing tools to exploit interdisciplinary research in the healthcare domain. Even if researchers were initially sceptical about being able to combine their different backgrounds, full support and guidance were offered by professionals of the field and by company staff that had experience in sharing interdisciplinary knowledge within the company. The project fostered a very close interaction amongst participants and researchers. The interaction was guaranteed not only through regular training but also through a dedicated knowledge platform and periodical meetings. The six researchers were required to team up and work together towards the results, ensuring a close interaction between the participating organizations, which shared responsibility for the quality of the research program.

At the end of the project, the involved staff developed new collaboration skills that resulted to be useful in other projects, in which the partners were involved. The research became more open to new ideas and suggestions, creating innovative solutions that helped to build the HEART platform. As underlined by the feedback from UniMC, new skills have been acquired in terms of mind set and problem solving. The administrative services, including the doctoral school offices, had to implement new procedures and solve issues in strong cooperation with the industry. Moreover, the HEART interdisciplinary approach fostered collaboration of UniMC researchers with those from the science, technology, engineering and mathematics (STEM) disciplines, which enabled the university to obtain funding for additional European

projects that are based on exploiting interdisciplinary perspectives for technological development. The collaboration with KU Leuven also boosted the establishment of new services for UniMC PhD students: a counselling service, a mentoring service and career advice also for non-academic paths.

As for KUL, the industrial relation network in the IoT/e-health domain was strengthened. Moreover, KUL was able to acquire funding for another Horizon 2020 aimed at managing the lifecycle of IoT devices. The solution will be validated in three industrial cases, one of which is in the domain of healthcare, built on the foundations developed in HEART. Furthermore, KUL was able to obtain secure funding for another Horizon 2020 project that aims at preserving fundamental rights in the use of digital technologies and e-health services. This project was developed in collaboration with UniMC and Maria Curie-Sklodowska University in Poland.

For *Philips*, all technologies and use cases that were built address actual challenges relevant for Philips businesses. As underlined in the company's feedback, even if the results of the HEART project are still in research phase, they contribute to many use cases and services developed within Philips. Philips recognized that HEART project was an opportunity to integrate social science and humanities perspectives with engineering disciplines. The integration of a multidisciplinary team of researchers with employees is expected to strengthen the firm's capacity to respond to the challenges of the Chinese market. Also, the company's partnership with Fudan University is strengthening relations with Chinese context and opening opportunities to partner with local institutions and firms.

In light of the above, the platform demonstrated how an industry–university partnership can contribute not only to the creation of new knowledge, in line with the findings of Ryan et al. (2018), but also to encourage interdisciplinary research in the healthcare sector.

Hence, we can conclude that the company and the two universities were able to leverage on interdisciplinary collaboration to derive a common vision on the role of IoT in the healthcare sector and design an effective plan of activities to develop the HEART platform. Key knowledge assets in the technical, legal and economic areas were embedded in the definition of the HEART platform.

7. Conclusions

The development of the HEART platform shows how the exchange of knowledge between organizations and researchers from different fields within a THM can support the development of sustainable solutions in the healthcare domain. Moreover, the steps of the AR methodology, adapted to the specific case, enabled to define the path for identifying and combining insights between social science and humanities perspectives with engineering disciplines.

The THM involving a company and two universities, as well as prestigious organizations and collaborative networks, in a founded European project acted as the driver to prompt collaboration from the planning till the design of the HEART platform. Designing the IoT platform allowed to uncover key challenges that need to be addressed from a technical (i.e. dealing with missing data), legal (i.e. complying with regulation and ethical standards) and economic perspective (i.e. identifying a profitable business model in China and Europe). These challenges were addressed by designing optimized ML models based on deep learning and regression approaches in a complex framework complying with different legal requirements and marketing inputs.

7.1. Theoretical implications

The findings of the research contribute towards enhancing the current literature on THM and OI by seeking an interdisciplinary perspective The integration of knowledge from different disciplinary domains can empower these innovative frameworks in order to guide the design of ground-breaking solutions that are able to match the growing needs of the healthcare sector.

The research also contributes to the on-going literature on Healthcare 4.0 by presenting innovative ML models to deal with unstructured and missing data, while complying with legal and ethical standards. Thus, the methods and strategies developed in the use cases can be re-used across future potential applications and contexts.

7.2. Practical implications

The study demonstrates that firms in the healthcare sector should foster interdisciplinary knowledge within their companies to deliver solutions that can comply with the multiple needs of the market. This can be done by being part of an effective THM. To be successful, a THM needs to be built on a set of criteria. First, stakeholders should carefully plan activities, milestones and outputs to clarify roles and strike coordination amongst the multiple actors involved. Second, it needs to be built on a learning-by-doing approach focused on the development of transversal skills, through which each actor is open to improve and revise its existing competences and knowledge. Third, open communications should be ensured among all THM members by developing appropriate mechanisms for the timely exchange of knowledge and feedbacks.

Concerning policy implications, national and European level funded projects should continue being based on collaborations that are rooted in a solid THM, requiring stakeholders to adopt new ways of working when designing innovative solutions. Then, discussion among different THM should be encouraged, even after the end of the project, as an opportunity to identify and compare methodologies and tools used to foster an effective collaboration among members.

7.3. Limitations and future avenues of research

As with all AR methodologies, the outcomes of the research cannot be generalized and need to be verified by comparing similar experiences. Thus, further cases in the healthcare sector need to be investigated in order to assess similarities and differences in the processes used to incentivize interdisciplinary research, remove barriers to collaboration, and develop a common language among disciplines. Moreover, while the HEART platform has been finalized, it is not possible to provide an analysis of its impact yet. Therefore, future research calls for understanding not only how collaboration and interdisciplinary research influence the design phase of innovative solutions, but also its impact on the implementation stage. Thus, longitudinal case studies based on multiple sources could be useful to follow up on the collaboration among members of a THM. Additionally, quantitative research could assess the impact of interdisciplinary projects by identifying and quantifying relevant outcomes for each member involved.

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