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FAITH

intelligent post-cancer support

Deliverable D2.1

Domain SotA & Data Assets

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FAITH Project Profile

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Acronym	**FAITH**
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Twitter	**https://twitter.com/H2020_Faith**
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Duration	**36 months**

FAITH Partners

List of participants

Participant No	Participant organisation name	Short Name	Country
1 (Coordinator)	WATERFORD INSTITUTE OF TECHNOLOGY	WIT	Ireland
2	UPMC Whitfield, Euro Care Healthcare Limited	UPMC	Ireland
3	Universidad Politécnica de Madrid	UPM	Spain
4	Servicio Madrileño de Salud	SERMAS	Spain
5	UNINOVA, Instituto de Desenvolvimento de Novas Tecnologias	UNINOVA	Portugal
6	Fundação D. Anna de Sommer Champalimaud e Dr. Carlos Montez Champalimaud	CF	Portugal
7	Deep Blue	DBL	Italy
8	Suite5 Data Intelligence Solutions Limited	SUITE5	Cyprus
9	TFC Research and Innovation Limited	TFC	Ireland

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Document Control

This deliverable is the responsibility of the Work Package Leader. It is subject to internal review and formal authorisation procedures in line with ISO 9001 international quality management system procedures.

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1.0	25/09/2020	Giuseppe Frau (DBL)	Final Version. Review. Executive summary and conclusions.

Executive Summary

***Objectives**:*

This document is aimed at summarising the current status of the domains covered by the FAITH project. It provides an overview of both research efforts previously made in similar challenges as well as the technology assets exploitable by the project consortium. The goal of the FAITH project is as follows:

"FAITH project is to provide an AI application that remotely identifies and analyses depression markers, using federated learning, to predict negative trends in people that have undergone cancer treatment. This concept would present healthcare providers with advanced warnings to allow timely intervention, and allow cancer patients to be more aware of their mental health situation and improve their quality of life."

It is evident from its goal that FAITH involves a wide range of social and technological complex domains. The SotA is the result of a joint effort across the consortium to collect resources and scientific results regarding each domain, and it is organised by topics that emerged from a) the original proposal, b) the material collected during the activities and c) the protocol description, which defines the primary and secondary endpoints of our studies.

The ultimate goal of the SotA is to remain constantly aware of what already exists and how the project can build on from the findings. As the involvement of fast-changing domains (e.g. Federated Learning) requires constant updates, the consortium has built an online dashboard that can be easily consulted and updated.

The results of this review are also of great importance for the external dissemination and communication activities in the project and will help the stakeholders to better frame the context of our challenges or possibly to contribute with resources of interest.

***Results**:*

The analysis focused on the topics of applied Artificial Intelligence to identify mental health conditions, federated learning, mobile apps and IoT related healthcare, sleep monitoring devices and methods, software libraries useful for the FAITH modules developments, and EU research projects similar to FAITH. Furthermore, data assets available to the consortium are described.

From the analysis, it is clear how FAITH preserves two points of uniqueness compared with products already in the market and with scientific works. These points are the target users, namely focusing on a specific category of individuals which are the post-cancer patients, and the usage of a federated learning approach to tackle the privacy issues. While the first aspect is a distinctive feature compared to existing and already functioning products, the usage of federated learning in such context is highly innovative and unexplored by far (even considering similar research projects). On the other hand, "traditional" AI models to detect mental health conditions are widely used and appear to provide promising results. A rich set of indicators is already defined for identifying depression and other related conditions.

Sleep monitoring technologies found in the review seemed to be used mainly in clinical contexts and less dynamic situations compared to the FAITH use cases. This suggests a need for more research to find more suitable devices. Finally, our publicly available online dashboard http://dashboard.h2020-faith.eu/ represents a tangible result of the efforts and an asset that can be exploited during the whole duration of the project.

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1 INTRODUCTION

The goal of the FAITH project is to provide an Artificial Intelligence (AI) application that remotely identifies and analyses depression markers, using federated learning, to predict negative trends in people who have undergone cancer treatment. This concept would present healthcare providers with advanced warnings to allow timely intervention and allow cancer patients to be more aware of their mental health situation and improve their quality of life. Thus, the FAITH framework envisages the collection of a range of potentially sensitive indicators such as physical activity, sleep quality, mental outlook (well-being), appetite and social activity to analyze and infer information about the mental status and quality of life of a person.

FAITH tackles privacy issues related to the collection of such data by using a Federated Learning approach that does not require the sensitive data to leave the person's devices to be analyzed.

Moreover, while part of the data can be collected in a "passive mode", namely, with no explicit interaction between the system and the user, information such as appetite, or mental outlook requires an active interaction, high engagement and motivation.

It is clear that FAITH involves a wide set of technologies, methodologies and challenges from different domains; the purpose of this deliverable is to identify such topics, summarize their current state of the art in an organic way. Furthermore, due to the importance of the data assets for the FAITH project, a dedicated chapter of the deliverable describes the current datasets which are potentially useful for our models.

After the present chapter and the abbreviations, the document presents the approach followed for the data collection and the analysis in Chapter 3. Subsequently, Chapter 4 describes the result of the state-of-the-art analysis organized by topic. Chapter 5 outlines the data assets available for the project, while Chapter 6 presents the online dashboard developed during the Task 2.1 to feed the state of the art material and presenting the results in a user-friendly way. Finally, in Chapter 7 we present our conclusions.

2 ABBREVIATIONS AND ACRONYMS

Abbreviation	Description
AI	Artificial Intelligence
D	Deliverable
EAB	External Advisory Board
EC	European Commission
EU	European Union
FL	Federated Learning
GDPR	General Data Protection Regulation
ICT	Information and Communications Technology
IoT	Internet of Things
ISO	International Organization for Standardization
IT	Information Technology
KPIs	Key Performance Indicators
ML	Machine Learning
PHQ-9	Patient Health Questionnaire – a multipurpose instrument for screening, diagnosis, monitoring and measuring the severity of depression.
QoL	Quality of Life
SotA	State of the Art
SVM	Support Vector Machine
WP	Work Package

3 APPROACH

For its multidisciplinary nature, the FAITH concept deals with a wide range of domains and complex challenges. Additionally, the state of the art associated with these challenges involves results of research projects, ready to market and proprietary products, smartphone apps, etc., thus, with very different maturity levels and methodological approaches. Capturing the status of such domains with a high level of detail is not in the scope of the present document, nevertheless, we aimed at finding and describing the most important results related to the main topics touched by FAITH. This chapter describes the approach followed to review the FAITH ecosystem, it describes the selected topics, the criteria for their selection and consequently the structure of the review in order to facilitate the understanding of the results.

3.1 Data collection

As previously mentioned, the information to be reviewed for the analysis involved many different domains and a variety of maturity levels. Importantly, relevant fields like federated learning, or AI supporting diagnosis are relatively new and fast-changing. For these reasons, we undertook a data collection and information gathering process. It

- involved all the partners in the FAITH consortium to address and cover the important aspects related to the project;
- was aimed at establishing a project asset which would be useful both internally and externally, thus building in parallel an interactive dashboard to present the results and be an instrument that could be easily be updated when new contributions are discovered and explored to facilitate development and awareness (see chapter 6).

The main topics selected for the review come from mainly three information sources, namely the project proposal (top-down), the resources collaboratively collected by the project partners (bottom-up/emerging topics) and the protocol description. The latter represents the description of the outcomes, the measures, and the people involved in the FAITH trials. Although the protocol description is not a formal deliverable for the project activities, the consortium recognized the need of such a document for a) better defining the primary and secondary outcomes of the studies, and b) getting the formal authorizations from the hospitals conducting the study. The document, which is currently under review by the consortium, will be attached to subsequent deliverables and will provide necessary information to help define the core requirements of the project.

3.2 Description of the topics

The following table lists each topic included in the review and describes the perimeter of each of them.

Topic Name	Description and Outline

Artificial Intelligence to support diagnosing mental health conditions	This topic involves all the attempts of automatic, semi-automatic diagnosis of mental health conditions using indicators referable to the FAITH ones, namely natural language processing, speech, body language, sleep quality.
Federated Learning	Since its novelty and its importance for the FAITH concept, this topic is specifically focused on the results related Federated Learning, not necessarily involving mental health applications.
Apps and IoT in healthcare	Mobile Apps, services, or projects dedicated to the mental health and quality of life of diverse categories of people, not necessary cancer survivors.
Software Libraries	This category includes the software libraries for supporting the less mature technological aspects of FAITH such as federated learning, models for detecting depression, activity monitoring / recognition etc.
Sleep Monitoring Devices / Technologies	FAITH aims at analysing sleep quality without employing wearable devices: this topic summarises the attempts, devices and technologies aiming at monitoring human activities through non wearable devices.
FAITH like projects / products	In this category we summarise the projects, products and studies that for their objectives and approaches present strong similarities with FAITH. This can be considered as potential synergies / source of lesson learnt for our study and, in future exploitations, potential competitors.
Data Assets	The data assets category presents the datasets, or data sources, or methodologies to produce data that can be used for training or evaluating the ML models.

4 SotA ANALYSIS

This Chapter presents the results of the review organized by topic. It starts by analysing the scientific efforts that aimed at applying artificial intelligence models to detect mental health conditions. It considers a set of indicators that have similarities with the FAITH ones, thus ranging from behavioural, to speech and text related ones. The review then moves naturally to Federated Learning by presenting the latest advances of this new field. Mobile apps and IoT related technologies are then reviewed with a focus on the healthcare domain. Software libraries potentially useful for the project developments are presented in Section 4.4, while Section 4.5 covers currently available sleep monitoring technologies. Finally, Section 4.6 is dedicated to the EU research projects presenting strong similarities with FAITH in terms of objectives, target users or approaches.

4.1 Artificial Intelligence to identify/support mental health conditions

There are many attempts to use AI to support the identification and treatments of mental health conditions, accordingly to [2]. This initially became notable around 1993 but a large increase of the number of works was observed only in the last decade with the growing importance of AI both transversally and in the healthcare domain. From the scientific literature point of view, a comprehensive review focused on the indicators for automatically detecting depression is provided by Morales work [1]. In their work, the authors summarise the definitions/models of depression mostly used in previous detection systems. Labelled datasets for instructing and validating models are also listed together with the related detection modality ranging from video/audio, text, or a combination of these. Each category of depression indicators is then analysed in terms of the previous scientific attempts and their results, providing a good source of information for the FAITH markers to be identified during our research. The categories listed include visual indicators (body movements, gestures, facial expressions etc.), linguistic and social indicators, speech indicators (related to the voice rather than to the language) and multimodal indicators as a combination of the previous ones. Compared to the FAITH objectives, it lacks indicators coming from sleep quality, appetite and physical activity. A variety of behavioural markers used in scientific research associated with depression is summarized in Table 1, below, produced in [3] and lists the signals together with their work references. Although Cummins work focuses on speech markers, it provides a comprehensive review of the objective markers used in literature.

Table 1 - From Cummins, list of behavioural signals to detect depression

Non Speech based behavioural signals associated with clinical unipolar depression, where ↓ indicates a reduction in the behaviour whilst ↑ indicates a increase the behaviour.

Behavioural Signal	Effect	Reference
Social Interaction	↓	Bos et al. (2002) and Hall et al. (1995)
Clinical Interaction	↓	Parker et al. (1990)
Gross Motor Activity	↓	Balsters et al. (2012), Parker et al. (1990), and Sobin and Sackeim (1997)
Slumped Posture	↑	Parker et al. (1990) and Segrin (2000)
Gesturing	↓	Balsters et al. (2012) and Segrin (2000)
Self-Touching	↑	Scherer et al. (2013c), Segrin (2000) and Sobin and Sackeim (1997)
Head-Movements (Variability)	↓	Girard et al. (2013) and Scherer et al. (2013d)
Facial Activity		
Mobility	↓	Parker et al. (1990) and Sobin and Sackeim (1997)
Expressivity	↓	Ellgring and Scherer (1996), Gaebel and Wölwer (2004), Girard et al. (2013), Maddage et al. (2009), Schelde (1998), and Segrin (2000)
Smiling	↓	Balsters et al. (2012), Schelde (1998), Scherer et al. (2013c), Segrin (2000), and Sobin and Sackeim (1997)
Eye Movements		
Eyebrow movements	↓	Balsters et al. (2012), Schelde (1998), and Segrin (2000)
Horizontal pursuit	↓	Abel et al. (1991) and Lipton et al. (1980)
Saccades	↓	Abel et al. (1991) and Crawford et al. (1995)
Visual fixation	↑	Sweeney et al. (1998)

Among the indicators considered in the FAITH concept and present in the scientific literature, language and voice seem to be the most explored. These two indicators complement each other the vocal and textual parts of the human, but they both have a great dependency with the cultural aspects. Therefore, the results of the research in these areas might be of limited applicability in the FAITH context. Cummins et al [3] however, tried to analyse the challenge with a focus on how common paralinguistic speech characteristics are affected by depression and suicidality and how these aspects can be used in automatic systems for supporting diagnosis.

A list of 16 depressed and suicidal databases is also described with the number of subjects, collection paradigm, clinical scores, rough content outline and a complete list of references. Regarding speech markers, Cummins identifies the following categories

- **Prosodic features**: *"they represent the long-time (phoneme level) variations in perceived rhythm, stress, and intonation of speech. Popular examples include the speaking rate, the pitch (auditory perception of tone) and loudness, and energy dynamics. In practice the fundamental frequency (F0, rate of vocal fold vibration) and energy are the most widely used prosodic features as they relate to the perceptual characteristics of pitch and loudness."*
- **Source features**: *"Source features capture information relating the source of voice production, the air flow from the lungs through glottis. They can either parameterize this flow directly via glottal features, or vocal fold movements via voice quality features. If being in a clinically depressed or suicidal mental state affects laryngeal control source features should therefore capture information relating to both conditions."*
- **Forman features**: Cummins illustrates a model of speech production where *"changes in vocal tract properties are affected by both an increase in muscle tension and changes in salivation and mucus secretion relating to changes in a speaker's mental state. If this model is valid, then these changes should be captured*

in detail by formant features, which contain information relating to the acoustic resonances of the vocal tract."

- **Spectral analysis features**: *"Spectral features characterize the speech spectrum; the frequency distribution of the speech signal at a specific time instance information in some high dimensional representation. Commonly used spectral features include Power Spectral Density (PSD) and Mel Frequency Cepstral Features (MFCCs)"*

Cummins concludes stating that given the wide clinical profile of both conditions it seems unlikely that a single biological, physiological and behavioural marker will be found; the best solution is most likely a multifaceted approach using carefully built classifiers sensitive to individual items from a depression or suicidal scale. The findings of their review suggest that speech will be a key component in the search for an objective marker.

Detecting depression through the analysis of the language used by a person also represents a research theme of interest for FAITH. Although providing a difficult challenge related by the specifics of the target language (FAITH will lead three pilots in Ireland, Spain, and Portugal, therefore with three different languages), it represents a topic of interest for the number of attempts in literature and the maturity reached by products that are already in the market. Mobile apps and software libraries supporting this function are in fact well documented online (see, for example [4,5,6,7] for mobile apps and [8] for software libraries).

Yazvadar et al. [9] used a semi-supervised approach to monitor clinical depressive symptoms using social media data with a model that was able to identify the symptoms with an accuracy of 68% and a precision of 72%. Their approach was based on the hypothesis that depressed individuals discuss their symptoms on social media (Twitter in this specific case) and these could be mapped against the PHQ-9 items [10]. The great availability of the data to process from the social media websites contributed to the popularity of the topic in the last years. These efforts however started around 2013, and the work of De Choudury et al. seems the most influential one. The authors from Microsoft explored the potential to use social media to detect and diagnose major depressive disorders and proposed a variety of social media measures to characterize depression behaviour such as language, emotion, style, ego-network and user engagement. Their results correlate depressed behaviours with *"lowered social activity, greater negative emotion, high self-attentional focus, increased relational and medicinal concerns, and heightened expression of religious thoughts".* The SVM classifier built with their approach reached an accuracy of 70% and privacy related concerns were raised by the authors regarding the availability and analysis of such data.

An additional source of information related to the usage of AI for managing depressive disorders, can be found in [2] where Tran et al. highlight the rise in the number of works from 2010 and point out, the focus of these efforts in the application of AI for identify clinical characteristics of depression (60% of the publications) and the most important specific research themes, namely diagnosis accuracy, structural imaging techniques, gene testing, drug development, pattern recognition, and electroencephalography (EEG)-based diagnosis. Although part of these approaches are out of the FAITH scope (drug development, for example) an important aspect highlighted by the work and affecting all the specific themes transversally is the lack of efforts to enhance and protect patient's privacy and confidentiality confirming the novelty introduced by the FAITH concept.

AI can be used not only to detect depression but also to mimic human interactions (e.g. chatbot). Natural Language Processing (NLP) is a core part of the FAITH concept, not only for allowing the extraction of speech and language indicators but also for facilitating the interactions and improving the user experience. Natural Language Processing has made a major leap in the past decade, both in theory and in practical integration into broadly deployed industry solutions. From interacting with virtual assistants to texting with a flight-booking chatbot to extracting insights from call centre interactions to analyse customer satisfaction levels, NLP is everywhere today. The objective of NLP for FAITH is to be able to better interact with the patient and to get information about that patient's mood and outlook. This task can be achieved by the usage of a smart device that would make easier the interaction, especially if that interaction is based on information retrieval by speech-to-text and responding with text-to-speech thus building a basic dialog that would avoid the usage of pen and digitizing devices. In fact, a recent Intel survey revealed 68 percent of Americans agreed that living in a home with smart devices would make their lives easier [12]. Consumers are beginning to show an increasing readiness to welcome speech in the smart home. Look at smart speakers and personal assistants: This year, 35.6 million Americans will use a voice-activated smart home device at least once per month, eMarketer estimates – a 128.9 percent increase over 2016. We want to be able to monitor a user's mood/outlook, one of the main ways hospitals do this is through the likes of Hospital Anxiety and Depression Scale - Depression (HADS-D). We believe NLP can streamline this process, making it feel engaging for the patient, and importantly giving the patient a voice. Some type of dialogs can be performed automatically like

"Are you feeling any pain today?"

The response can be analysed by the NLP component in detecting keywords such as Yes, No, Fine, Worse, Pain, Suffering, etc.

For that a number of engines are available such as those of Amazon Comprehend, Google Cloud Natural Language and Watson Natural Language Understanding from IBM. There are also a range of powerful, open-source libraries such as torchtext and SpaCy.

In response to that, the NLP component can orchestrate a proper answer and build from there the next question. In general, the NLP approach aims at facilitation of the human computer interaction along with the need to provide the most accurate and assertive response to the human user, in diverse scenarios, with a relevant role when it comes to the wellbeing and the health related episodes.

4.2 Federated Learning

In 2017, Google introduced Federated Learning (FL), "a specific category of distributed machine learning approaches which trains machine learning models using decentralized data residing on end devices such as mobile phones." Federated learning opens up a brand-new computing paradigm for AI. As compute resources inside end devices, such as mobile phones, are becoming increasingly powerful, especially with the emergence of AI chipsets. AI is moving from clouds and datacentres to end devices. Federated learning provides a privacy-preserving mechanism to effectively leverage those decentralized compute resources inside end devices to train machine learning models. Considering that there are billions of mobile devices worldwide, the compute resources accumulated from those mobile devices are way beyond the reach of the largest datacentre in the world. In this sense, federated learning has the potential to disrupt cloud computing, the dominant computing paradigm today [16].

Before the start of the actual training process, the server initializes the model. Theoretically, this can be done arbitrarily, by using any of the common neural network initialization strategies or the equivalent for other model types. In practice, it is a good idea to use publicly available data to pretrain the model.

Since its inception in 2017, Federated Learning has garnered considerable attention due to its promise of distributed, private, personalised machine learning. In a short time frame, it has moved from a research topic in Google to recent adoption by TensorFlow and other open-source libraries. Although an area of very active research, it has already been deployed as a scalable production system. While federated learning offers many practical privacy benefits, providing stronger guarantees via differential privacy, secure multi-party computation, or their combination have been identified as promising areas for further research[29].

The other key areas to be addressed have been identified as 1) Bias, 2) Convergence Time, 3) Device Scheduling, 4) Bandwidth, and 5) Federated Computation.

With Federated Learning as the core of FAITH, we have directed the majority of our research focus here, as we firmly believe it has the most potential not just for scientific impact, but also commercial and societal impact.

We have identified three research strands that together, will validate FL as the prime means of deploying privacy-preserving, communication efficient AI to edge devices:

1. Standardised FL models
2. Differential Privacy and Encryption
3. Model Compression

Standardised FL Models

FL was created with a clear purpose in mind, to enable machine learning algorithms on personalised, distributed data. It is such a good fit for privacy-sensitive healthcare applications, but to achieve widespread adoption it will have to be accessible and reusable. Over the past 10 years, healthcare data has moved from being largely on paper to being almost completely digitized in electronic health records. But making sense of this data involves a few key challenges. First, there is no common data representation across vendors; each uses a different way to structure their data. Second, even sites that use the same vendor may differ significantly, for example, they typically use different codes for the same medication. Third, data can be spread over many tables, some containing encounters, some containing lab results, and yet others containing vital signs.

The Fast Healthcare Interoperability Resources (FHIR)[30] standard addresses most of these challenges: it has a solid yet extensible data-model, is built on established Web standards, and is rapidly becoming the de-facto standard for both individual records and bulk-data access. However, to enable large-scale machine learning, we needed a few additions: implementations in various programming languages, an efficient way to serialize large amounts of data to disk, and a representation that allows analyses of large datasets. To address these issues Google open-sourced a protocol buffer implementation of the FHIR standard[31].

4.3 Mobile Apps & IoT in Healthcare

A central component of FAITH is obviously the user's smartphone, both as an interaction endpoint but also as a sensor suite. Not long ago the options for deploying an app to a smartphone were quite limited. Today, however, there are numerous competing approaches e.g. Progressive Web Apps, native apps, React Native, etc.

This application has several responsibilities, one of which is the gathering of activity data directly from the smartphone's sensors. Both GPS and accelerometer data will be used to represent a user's activity level. A core design feature of the application is extensibility, as the types of ML models that might be deployed, or the range of inputs for such models could easily change over time. One such example, not currently considered by FAITH, but may be desirable by the adopters of the FAITH framework would be visual emotion recognition (Chen, 2018). In the remainders of this section, we review a set of mobile applications that include features or have objectives that are in common with FAITH. Subsequently we extend the analysis to the IoT domain.

Table 2 - List and descriptions of mobile apps related to FAITH

Title	Topics	Description	Relevance for FAITH
Moodpath	depression, other mental disorders	Moodpath (Your Mental Health Companion) is your personalized mental health companion and supports you in phases of stress, depression, and anxiety. https://mymoodpath.com/en/	The app is able to detect mental disorders, scientifically validated. In this aspect is very similar to FAITH. Detection is based on interacting with the users three times a day and by following an emotional journal. Does not cover AI and most of the markers in FAITH.
Youper	AI, depression, nlp	app for iOS and Android uses AI chatbot technology to help users talk through their symptoms, behaviors, and patterns. The company calls Youper an "emotional health assistant," that provides personalized feedback and insights based on what it learns in daily text-based conversations with users. https://www.youper.ai/	App for tracking mood over time and improving mood based on AI and conversations. Identifies emotional profiles based on AI algorithms, uses NLP to interact. Does not provide medical diagnosis /treatments. Processes natural language and interacts through it. Can be useful for some interaction between patients and faith
Mindstrong	mental health, biomarkers, indicators	Online mental health care. A service that include in the approach (based on app) the tracking digital cognitive biomarkers https://mindstrong.com/	Approaches the problem with the interesting the idea of digital biomarkers. includes an app to measure mood. Most of the tools the service is based on, however, are devoted to providing psychological support from trained psychologists or psychiatrists through the app.

CompanionMX	AI, detecting-depression, speech, approach	The Companion™ mobile monitoring system passively tracks behavioral indicators of mental health. Moreover, Companion's acoustic biomarker—a proprietary analysis of voice features—provides unique and proven insights into mood states. A smartphone app that use AI to detect depression. The company building the app is CompanionMX, based in Boston, MA. A neuroscientist (and psychiatrist) is the Chief Medical Officer. Securely records voice features and phone meta-data indicative of four digital biomarkers correlated with symptoms of mental health. Converts data from the smartphone app and turns it into scores on four key dimensions: 1) depressed mood; 2) diminished interest; 3) avoidance; and 4) fatigue https://companionmx.com/	CompanionMX is an existing product and its features related to depression and quality of life have a high match with the FAITH ones. Interesting application allows patients being treated with depression, bipolar disorders, and other conditions to create an audio log where they can talk about how they are feeling. The AI system analyzes the recording as well as looks for changes in behavior for proactive mental health monitoring. Very interesting, and in line with FAITH's goal, although focused on a broader target base (not just cancer patients). "But it is often very difficult for doctors to know how patients are doing between clinic visits". There is a dashboard for clinicians too, to monitor trends of patients' mental health status. Apparently, they also conducted a randomized control trial with real patients in a hospital that showed that the use of the app improved patients' health. Results have not been published yet though.
Helm	depression, approach, engagement	Helm is an app that gamifies stress/anxiety/depression management in an actionable manner to provide relief. https://github.com/chuabingquan/helm	Interesting approach to engage users with depression problems (interacting with faith)
WoeBot	AI, depression	WoeBot launched in the summer of 2017 and is referred to as an automated conversational agent, also known as a chatbot. It is designed to offer convenient care to those struggling with depression by mimicking human conversation, offering self-help related guidance and companionship to its users. https://woebot.io/#faq	Processes natural language and interacts through it. Can be useful for some interaction between patients and faith

Wysa	AI, depression, support, nlp, emotions	Wysa is an artificial intelligence-based, "emotionally intelligent" bot that the company says can "help you manage your emotions and thoughts." Like WoeBot, Wysa's designed based on principles of CBT to help users challenge and change thoughts and behaviours. Wysa also incorporates dialectical behavioural therapy (DBT), meditation practices, and motivational interviewing into chats. https://www.wysa.io/	Processes natural language and interacts through it. Can be useful for some interaction between patients and faith. Also provides a channel with professionals
Tess - X2AI	AI, depression, nlp	Tess - X2AI's Tess is described as "a psychological AI that administers highly personalized psycho-education and health-related reminders on demand.". The program is a text-based messaging conversation that users can access through Facebook Messenger, SMS texting, web browsers, and smartphone apps. https://www.x2ai.com/	NLP is the core of the application, it mimics familiar channels of interactions, like texts
Ginger.io	depression, approach, engagement	On-demand access to behavioral health coaching, video therapy, and video psychiatry that's clinically proven to reduce symptoms of stress, anxiety, and depression. Its algorithms analyze the words someone uses and then relies on its training from more than 2 billion behavioral data samples, 45 million chat messages and 2 million clinical assessments to provide a recommendation. https://www.ginger.io/	Good example of how to support a person affected by depression with remote but tailored resources like videos and remote professionals

Strava	smartphone, monitoring, gamification, social media	Strava is a fitness-tracking app for runners, cyclists, and swimmers who are looking for a bit of competition. In Strava you compete against yourself or other people who have run, biked, or swam the same segments that you have. The app uses the GPS from your phone or a connected device to track where you go and how fast. Then it analyzes yours and everyone's data to see where you overlapped to compute a segment leaderboard. https://www.strava.com/	Related to activity tracking within FAITH, e.g. as help with the mobile app that will be used to track mobility levels using the in-built smartphone GPS and accelerometer sensors.
Fitbit Coach	smartphone, engagement, support, audio-video	Fitbit Coach is a good workout-on-demand app for people who want a real human in a video to talk them through their routine. Whether you own a Fitbit tracker or not, you can use the Fitbit Coach app (formerly called Fitstar) to follow along with workout videos that you can do nearly anywhere. There are all kinds of options, from stretching routines to stair workouts. https://www.fitbit.com/eu/fitbit-premium	Related to activity tracking within FAITH, e.g. as help with the mobile app that will be used to track mobility levels, sleep quality, using the in-built smartphone GPS and accelerometer sensors.
Google Fit	smartphone, monitoring, wearable, platform	Google Fit is a health-tracking platform developed by Google for the Android operating system, Wear OS and Apple Inc.'s IOS. It is a single set of APIs that blends data from multiple apps and devices. Google Fit uses sensors in a user's activity tracker or mobile device to record physical fitness activities (such as walking, cycling, etc.), which are measured against the user's fitness goals to provide a comprehensive view of their fitness. https://www.google.com/fit/	Related to activity tracking within FAITH, e.g. as help with the mobile app that will be used to track mobility levels using the in-built smartphone GPS and accelerometer sensors.
Endmondo	smartphone, monitoring	Endomondo is a social fitness network created by Endomondo LLC which allows users to track their fitness and health statistics with a mobile application and website. Endomondo launched in 2007 with the goal of motivating people to lead healthier lives. https://www.endomondo.com/	Related to activity tracking within FAITH, e.g. as help with the mobile app that will be used to track mobility levels using the in-built smartphone GPS and accelerometer sensors.

Runtastic	smartphone, monitoring	adidas Running by Runtastic or formerly named Runtastic is an Austrian mobile fitness company that combines traditional fitness with mobile applications, social networking and elements of gamification as a logical reaction to the Quantified Self movement. Runtastic develops activity tracker apps, hardware products, and services, such as online training logs, detailed data analysis, comparisons to other users, and many more functions to help users improve their overall fitness. https://www.runtastic.com/	Related to activity tracking within FAITH, e.g. as help with the mobile app that will be used to track mobility levels using the in-built smartphone GPS and accelerometer sensors.
Garmin Connect	smartphone, monitoring, wearable, platform	On mobile or web, Garmin Connect is the tool for tracking, analyzing and sharing health and fitness activities from your Garmin device. Garmin Connect displays your vital health data and entries for easy viewing. https://connect.garmin.com/	Related to activity tracking within FAITH, e.g. as help with the mobile app that will be used to track mobility levels using the in-built smartphone GPS and accelerometer sensors.
Apple Activity	smartphone, monitoring, wearable, platform	The Activity app is the fitness tracking element of the Apple Watch, and keeps tabs on whether you're getting enough exercise per day. It differs from most activity trackers by dispensing of step goals. Instead, the Apple Watch has three targets: Move, Exercise and Stand. https://www.apple.com/shop/buy-watch/apple-watch	Related to activity tracking within FAITH, e.g. as help with the mobile app that will be used to track mobility levels using the in-built smartphone GPS and accelerometer sensors.
S5 Personal Activity Analytics	smartphone, analytics engine, platform	The overall infrastructure is based on a smartphone app that is able to fetch data from smartphone data hubs (like Apple Health) and the main analytics platform which can also connect to third party APIs for data/activity data retrievals, where data is offloaded and analysed. The latter can either showcase individuals' data, or grouped anonymised data of individuals sharing some common characteristics, titled as "Personas". The recipient of those data are organisations and users who are selected as data sharing recipients from the different individuals. At this moment the overall solution is being refactored.	Relevant for the activity tracking solution to be implemented in WP5

Nutrition & Physical Activity app	nutrition, physical activity, gamification	Nutrition and physical activity app for promoting a healthy lifestyle. This app provides a customizable diet and a physical routine according to the user interest, preferences and needs. It is based on user profiles and supported by professionals	Supporting T5.5 and part of background of UPM
Nevermind app	smartphone, depression, mental health	Telemonitoring system gathering data from app and a wearable sensor. Web portal for health professional to see results, export and see analytics. App for patient to monitor emotions and practice mindfulness. Promotion of physical activity, sleep hygiene, healthy diet. https://play.google.com/store/apps/details?id=es.upm.tfo.lst.nevermind	Related to depression and mental health, and employs indicators like questionnaires and sleep quality to assess mental health status

The overall picture shows that the set of features involved in the FAITH concept can be found in other existing products. However, the complete combination of features is rarely present in a single application with the only exception of CompanionMX that seems to cover the same aspects. Furthermore, there are two key points that are not present in the existing apps ecosystem, namely the usage of the federated learning approach to protect users' privacy, and the post-cancer patients as target users.

Mobile phones and related apps can now be seen as part of a wider constellation of devices and technologies that strongly interacts with the IoT segment. The pervasiveness of computational devices is implicit in many of the objects we use daily in our routines even if most of the times we don't need to know or understand what is behind the usage of electronic gadgets or something so simple as taking an automatic elevator or having the temperature of the room adjusted to our needs.

The concept of Internet of Things (IoT) refers to any physical object embedded with technology capable of exchanging data and is applicable in numerous areas, including healthcare, but this broad term covers all non-computer and non-phone Internet connected devices. In the case of healthcare, the usage of the IoT paradigm allows for the healthcare centres to function more competently thus managing more efficiently people and assets, resulting in a clear benefit in better care for patients. In fact, IoT approaches are pegged to create a more efficient healthcare system thus providing benefits in terms of time energy and cost. One area where the technology could prove transformative is in healthcare, with analysts at MarketResearch.com claiming the sector will be worth $117 million by 2020. By embedding IoT-enabled devices in medical equipment healthcare professionals will be able to monitor patients more effectively and use the data gleaned from the devices to figure out who needs the most hands-on attention. In other words, by making the most of this network of devices healthcare professionals could use data to create a system of proactive management – as they say prevention is better than the cure[44].

The usage of devices worn by patients, most of the times in the form of common electronic devices, also known as gadgets, or specifically designed medical portable devices (e.g. Holter, Blood Pressure Measurements) can provide simultaneous reporting and monitoring of the patient's health status. These kind of measurements can save lives in critical cases as in heart attack or asthma crisis where real-time reporting will enable prompt save and rescue measurements by health emergency services. In many cases, IoT devices can make use of an app that makes a preliminary reasoning over collected and reports, based on collected data referring to physiological measurements such as: ECG, blood pressure, SpO2 and blood sugar levels. At the same time, digitising and streamlining the sharing of health data has the potential for dramatic gains in efficiency significant cost savings – Goldman Sachs recently estimated that Internet of Things (IoT) technology can save billions of dollars for asthma care. It's a challenging dichotomy, as CIOs continue to look for ways to manage the risks of IoT and capture the benefits. Keeping patients in a hospital setting is expensive. The average daily cost for a single inpatient was over $1,700 in 2013, according to the Kaiser Family Foundation. Remote monitoring products, such as the BodyGuardian Remote Monitoring System, give healthcare pros the option to move patients to their home and retain monitoring of their status by doctors and nurses[1]. Benefits from the adoption of IoT in Healthcare are verifiable in different events as it reduces emergency room wait time, it improves personal management of the whole hospital ecosystem by tracking patients, staff and inventory of disposables and equipment. In terms of safety, IoT devices that track medication stocks and each patient intake will improve the drug management by ensuring that each person ingests the prescribed dose at the right time and stocks are updated properly. In terms of logistics and availability, especially relevant for emergency events, IoT based management ensures the availability of critical hardware on time where needed.

4.4 Software Libraries

TensorFlow is one of the predominant machine learning libraries, and for some time has provided functionality that allows for the deployment of machine learning models to mobile devices, e.g. TensorFlow Serving, TensorFLow Lite . Recently they have also released TensorFlow Federated, an open-source framework for ML on decentralised data. There are, however, other compelling open-source alternatives e.g. OpenMined. Both offerings are directly compatible with the Keras and PyTorch frameworks that are expected to be used for ANN development.

In addition to the FL libraries mentioned above, there also exists a set of libraries that implement a complementary technique, known as Differential Privacy, e.g. WhiteNoise, TensorFlow Privacy and PySyft . Differential privacy is referred to as the gold standard of privacy protection. By formalizing what privacy means, we can analyse how well the learning algorithm respects privacy. To employ this technique to Federated Learning, the notion of privacy is adapted to a user level: It should be very hard to tell whether a user contributed to the training of the model. This is done using a stochastic framework. By adding noise to update data shared by the user, the reports of individuals become much harder to analyse, while the noise can be estimated well for the aggregated data [17]. A group of Samsung researchers have demonstrated the applicability of this technique to Federated Learning [18].

4.5 Sleep Monitoring Devices / Technologies

Frequency-modulated continuous waveform (FMCW) radars are becoming increasingly popular in diverse domains of application (e.g. health, self-driving cars). The goal behind such devices and applications relies on the premise that it is possible to monitor an object's movement and, by consequence, an object changes of geometry without placing sensors or even touch the object. In regards to the human body, the main objective would be; to be able to monitor displacement or even vital signs without placing sensors over the person's body as presented by Vital Radio a wireless sensing technology that monitors breathing and heart rate without body contact, an ongoing research at MIT (Adib, et al., 2015). The system is based on the same principles or radar that is used in ships and also used by some animals. (e.g. bats and dolphins). The electronic setup needs a wireless signal source which is commonly used and a receptor for the reflected waves. Then, it is necessary to solve some problems such as isolating reflections from other users and from the environment (e.g. walls, furniture) and identify the relevant signals from breath and heartbreak. This can be achieved with an electronic element that performs analysis (e.g. FFT using Fourier

[1] https://www.cio.com/article/2981481/how-the-internet-of-things-is-changing-healthcare-and-transportation.html

transforms). Leveraging the FMCW can be accomplished using Universal Software Radio Peripheral (USRP), a set of software-defined radios, which is comprised by a motherboard, for processing baseband signals, and a daughterboard modular front-end, used for analogue operations, filtering and signal modulation. The open source USRP hardware driver is widely supported by the most common operating systems platforms and frameworks and also accessible through a native C++ API. Once the device is ready to identify and isolate the signals from HR and respiration, it is possible to store and analyse in a smartphone of use it to upload raw data or result from an initial analysis. The system can also be used to track indoor movements, to make an assessment of movement patterns. Those two assessment types; sleep analysis and displacement patterns are two of the main drivers to identify a person's health status within the functional execution of the FAITH Framework.

FMCW radars are the initial solution identified during the proposal stages. While they are potentially able to monitor sleep and movements patterns in a given space, their usage might introduce other challenges, such the presence of other people other than the target subject, their cost, and the technological integration with the FAITH ecosystem. For these reasons, other monitoring solutions are now being explored by the consortium. Such devices are still in the "contact free" range of solutions, namely they do not require direct contact with the person in order to function (in opposition to the wearable segment of devices). Specifically, the current device is the EMFIT, which is able to detect heart rate variability and sleep quality through a sensor placed between the bed structure and the mattress.

"EMFIT QS™[2] relies on ballistocardiography, a technique for sensing the sudden ejection of blood into the great vessels with each heartbeat, and breathing movement analysis."

EMFIT provides a scientific research programme that allows scientists to interact with the device and pull the collected data through a set of convenient APIs.

4.6 Research projects similar to FAITH

This section summarizes the EU research projects that for their objectives, target users or technologies present good similarities with the FAITH concept. Both ongoing and closed projects are reviewed. Similarly to the mobile apps, Table 3 includes a column to describe the entry, a list of the topics tackled, and why each project is relevant for FAITH. This is a subset of the projects listed in the FAITH online dashboard (see section 6), obtained selecting the most relevant ones.

From the list, it seems clear how a higher number of projects -compared to the products and apps- come close to the FAITH concept, especially in the target users and the privacy issues. In fact, there is a number of projects targeting but not limiting to post-cancer patients to improve their QoL: individuals with other important deceases or ageing persons are also included.

[2] https://www.emfit.com/

The projects identified can be used as a source of information about specific and general results, methodologies and technical solutions but also to build synergies for dissemination activities to raise awareness regarding the FAITH goals and outcomes.

Table 3 - EU research project similar to FAITH in their objectives / target users /approach

Project Title	Topics	Description	Relevance for FAITH
SOMA Analytics	stress, biomarkers, burnout, app, depression, speech, ai	Chronic Stress Biomarkers for Early Detection and Prevention of Burnout. The project focuses on the early detection of work-related psychological stress resulting in negative health outcomes, such as burnout or depression. One of the key innovations of the project is the use of speech analysis to evaluate chronic stress by using a dual approach: first, recognize stressed speech using two nonlinear feature models and second, recognize emotion profiles in order to assess mental resilience. The analysis follows a machine learning approach by identifying relevant features to build classifiers which are then trained on a suitable data set. https://cordis.europa.eu/project/id/663269	EU funded project (closed) that is partly in line with FAITH, in that it wanted to develop ML algorithms for early detection of depression as an outcome of stress from speech, and to use smartphones.
LUCY	depression, other mental disorders, chronic diseases, biomarkers, app, depression, monitoring	Early detector of comorbid depression. Chronic patients suffering from mood disorder and depression comorbid to other pathologies or drug treatments receive poor preventive screening, insufficient early diagnosis and follow-up; Lucy is a cross-platform cloud environment continuously collecting biomarkers belonging to psychic and relational life of the person, like anxiety, depression, pain, disability, relational impairment, using screening tools officially validated by medical practice. An advanced relational system, characterized by very low cost for the patient, elaborates information and translates it into objective and communicable data available to the team of attending physicians, providing continuous, updated patient monitoring, through data-mining and smart on the go doctor interface. https://cordis.europa.eu/project/id/697269	EU funded project (closed) that is partly in line with FAITH, in that it aims to gather a variety of biomarkers to support preventive screening of depression and other mood disorder in chronic patients.
Limbic	AI, wearable, app, library, vocie, text, biomarkers, emotions, monitoring , emotions	An API for Emotional Intelligence. API platform that senses emotional state using signals from the user: facial expression, voice, text, and importantly, physiological signals from wearables. The software development kit (SDK) is one line of code that sits inside client apps. The code detects which data sources are available (e.g. camera, microphone, text corpus, and wearable heart sensor) and our proprietary machine learning algorithms analyse these to return predictions on the user's emotional state.	EU funded project (closed) that is partly in line with FAITH, in that it aims to develop an API platform to detect and predict emotional states from several biomarkers sensed from different sources through a smartphone.

		Content recommendations for your current mood, personalised app notifications, mental health monitoring - Limbic is an enabling technology with applications across a range of sectors. https://cordis.europa.eu/project/id/837234	
PRISM	biomarkers, depression, other mental disorders, library, datasets, app	Psychiatric Ratings using Intermediate Stratified Markers. This project aims to develop a quantitative biological approach to the understanding and classification of neuropsychiatric diseases to accelerate the discovery and development of better treatments for patients. Focus on Schizophrenia, Alzheimer's disease, and Major Depression . https://cordis.europa.eu/project/id/115916	EU funded project (closed) that aims at improving our understanding and classification of depression and other mental diseases with similar symptoms, based on several biological indicators sensed using different technologies including smartphone sensors. It is relevant to FAITH in that the use of some data collected with smartphones is included from a clinical cohort of patients.
KONFIDO	library, privacy, datasets	Secure and Trusted Paradigm for Interoperable eHealth Services. KONFIDO advances the state of the art of eHealth technology with respect to four key dimensions of digital security, namely: data preservation, data access and modification, data exchange, and interoperability and compliance. To address the challenges of secure storage and exchange of eHealth data, protection and control over personal data, and security of health related data gathered by mobile devices, KONFIDO takes a holistic approach – i.e. one targeting all the architectural layers of an IT infrastructure, and specifically: storage, dissemination, processing, and presentation. https://cordis.europa.eu/project/id/727528	EU funded (closed) project that aimed at developing a framework to secure eHealth services using sensitive data.
MindCare	AI, mental health, smartphone, monitoring, wearable, other mental disorders, depression, app	AutoMatic and Personalized Mental HealthCare Solution. A mHealth solution that addresses the current lack of a real-time heath status monitoring for mental disorder patients. MindCare is a smartphone App that: 1) passively gathers data through a wearable device about the patient; 2) transforms the data into interpretable information using Artificial Intelligence (AI) for doctors, patients and caregivers; and, 3) integrates and displays the patient information, providing personalized information so that doctors and caregivers can quickly change the patient treatment or intervene at the right time. https://cordis.europa.eu/project/id/865620	EU funded project (closed) that is partly in line with FAITH, in that is aims to use data gathered passively through smartphones by a dedicated app, analyzed by AI models, to inform patients, doctors and caregiver on mental health status, with the ultimate aim of improving treatment effectiveness and timeliness.

HYGGii	AI, mental health, smartphone, monitoring, wearable, support, app	Described as: The therapist in your pocket - AI assisted ecosystem for enabling a patient-centric approach to mental health. The EU-funded HYGGii project autonomously provides first-level assistance, personalised support and orientation to individuals suffering from mental problems. Its artificial intelligent algorithms are designed to acquire knowledge from multi-language inputs and from smartphone-embedded and wearable sensors, to then provide assistance through a string of means including text/audio answers and VR-interfacing. More so, HYGGii is integrated into system of real professional health care service providers across Europe able to further assist patients beyond. https://cordis.europa.eu/project/id/877559	Eu funded project (closed) to develop an AI based app to support patients with mental health issues. It is relevant in the fact that is uses AI, and data sensed by smartphone (textual and non-verbal) to detect when it is necessary to provide automatic support.
NEVERMIND	smartphone, wearable, depression, monitoring, activity, app	NEurobehavioural predictiVE and peRsonalised Modelling of depressIve symptoms duriNg primary somatic Diseases with ICT-enabled self-management procedures. NEVERMIND sets out to empower people who suffer from symptoms of depression related to a serious somatic disease by placing them at the center of their mental healthcare. Equipped with just a smartphone and a lightweight sensitized shirt, patients seeking care and treatment for their mental illnesses interact with these devices that collect data about their mental and physical health, to then get effective feedback. Lifestyle factors, i.e. diet, physical activity and sleep hygiene, play a significant mediating role in the development, progression and treatment of depression, and in NEVERMIND will be monitored by a real-time Decision Support System running locally on the patient's smartphone, predicting the severity and onset of depressive symptoms, by processing physiological data, body movement, speech, and the recurrence of social interactions. https://cordis.europa.eu/project/id/689691	EU funded project (closed) that is partly in line with FAITH, in that it wanted to develop a system based on a smartphone app for the detection/prediction of depression episodes from speech, movement and other type of behavioural data monitored by the system locally run on the phone.
ASCLEPIOS	library, privacy, health data	Advanced Secure Cloud Encrypted Platform for Internationally Orchestrated Solutions in Healthcare. The vision of ASCLEPIOS is to maximize and fortify the trust of users on cloud-based healthcare services by developing mechanisms for protecting both corporate and personal sensitive data.. ASCLEPIOS also offers the ability to users to verify the integrity of their medical devices prior using them while at the same time receiving certain guarantees about the trustworthiness of their cloud service provider. Furthermore, ASCLEPIOS offers a novel solution through which healthcare practitioners and medical researchers are able to calculate	Ongoing EU funded project to develop cloud based cryptographic approaches to protect patient privacy and sensitive data used by eHealth applications. Possibly relevant to the FAITH modules for privacy.

		statistics on medical data in a privacy-preserving way. https://cordis.europa.eu/project/id/826093	
MENHIR	library, platform, mental health, monitoring, conversation, support, app	Mental health monitoring through interactive conversations. The MENHIR project aims to research and develop conversational technologies to promote mental health and assist people with mental ill health (depression and anxiety) to manage their conditions. https://cordis.europa.eu/project/id/823907	Ongoing EU funded project aimed at developing an app to monitor depression status and provide help if necessary, using conversation. Although the main focus is on assisting patients, and the type of data seems to be mainly verbal data, the conversational approach might be used also in FAITH.
BD4QoL	ai, big data, cancer, quality of life, mental health, monitoring, smartphone, indicators, app	Big Data Models and Intelligent tools for Quality of Life monitoring and participatory empowerment of head and neck cancer survivors. Head and neck cancer can take away a patient's "right to feel human," and its impact on physical appearance, physical functioning, psychological status and general quality of life (QoL) can be devastating. BD4QoL objective is to improve HNC survivor's Quality of Life through person-centred monitoring and follow-up plan by contribution of artificial intelligence and big data unobtrusively collected from commonly used mobile devices, in combination with multi-source clinical, -omic, socioeconomic data and patients reported outcomes, to profile HNC survivors for personalized monitoring and support. The analysis of QoL indicators collected over time will allow to early detect risks, prevent long-term effects of treatment and inform patients and caregivers for personalized interventions. https://cordis.europa.eu/project/id/875192	Ongoing EU funded project that is in line with FAITH since it targets cancer patients, with the aim of monitoring and quality of life through several indicators collected using smartphone.
PERSONA	monitoring, mental health, smartphone, library, depression, other mental disorders, sensors, speech, app	PERSONAlised Health Monitoring System. Depression is one of the most prevalent health problems in Europe. The project researches algorithms based on the combination of aforementioned metrics which enable accurate and objective diagnosis. It will implement these algorithms on a lightweight mental health monitoring platform based on a smartphone and body sensor network which can be used during daily life activities. He will use novel methods of Affective Computing thus maintaining and enhancing the candidate's position at the forefront of advances in this field. This project	EU funded ongoing project very much in line with FAITH in the fact that is aims to develop an app to detect and predict depression from different type of data gathered by the smartphone, including data also considered within FAITH such as speech.

		will provide a new platform that helps to expand mental healthcare into the homecare domain where existing treatment methodologies have not yet demonstrated substantial effectiveness as compared to in-ward settings. Also the ability of long-term monitoring of mental health has the potential to help in the pre-clinical assessment, early diagnosis, and treatment prediction of other than depression severe disorders like bipolar disorder, where a patient exhibits extreme swings in mood related to manic and depressive episodes. https://cordis.europa.eu/project/id/327702	
mPOWER	cancer, fatigue, monitoring, app	Mobile platform to empower cancer patients with fatigue. An innovative mobile application for self-management addresses CRF to improve patients' quality of life. CRF is a distressing and persistent condition related to cancer and cancer treatments that interferes with patient functioning. Unlike regular fatigue, CRF has an erratic onset, prolonged recovery periods and is not proportional to recent activity. Moreover, patients with CRF often experience depression and anxiety. The EU-funded mPOWER project combined two decades of psychological interventions and academic research to develop the first mobile application that addresses CRF. The "Untire" application aims to transform the lives of cancer patients and survivors through effective, digital support to reduce fatigue and improve quality of life. Users record their energy and fatigue on a weekly basis, which gives them insight on energy expenditure and helps them understand the factors responsible for CRF. It also provides stress-reduction activities, motivational tips and physical exercises to help users build their physical strength. https://cordis.europa.eu/project/id/756641	EU funded (closed) project that aimed at building an app to help cancer patients to manage with fatigue that is related to the disease or its treatment. It is relevant first of all because of the target population and the relationships between the issue and depression; would also be relevant because the project build a smartphone app.
MUSKETEER	AI, privacy, federated learning, libraries, platform, library	Machine learning to augment shared knowledge in federated privacy-preserving scenarios. MUSKETEER aims to create a validated, federated, privacy-preserving machine learning platform tested on industrial data that is inter-operable, scalable and efficient enough to be deployed in real use cases. MUSKETEER aims to alleviate data sharing barriers by providing secure, scalable and privacy-preserving analytics over decentralized datasets using machine learning. Data can continue to be stored in different locations with different privacy constraints, but shared securely. https://cordis.europa.eu/project/id/824988	EU funded project (ongoing) aimed at developing a federated, privacy-preserving, machine learning platform. Clearly relevant for the FAITH project that includes in the scope work on federated-learning as a privacy-preserving ai framework. The scenario the project intends to devise could be also interesting to analyse.

LifeChamps	cancer, quality of life, ageing, AI, big data, platform, study, app, platform	A Collective Intelligence Platform to Support Cancer Champions. LifeChamps delivers a novel, context-aware and large-scale analytics framework capable of delivering multi-dimensional Quality of Life (QOL) support to all the different cancer life champions during and after their treatments. LifeChamps is providing support to middle aged and older (pre-frail and frail) cancer patients, as well as their caregivers and healthcare professionals, with an integrated Big Data-driven solution capable to improve their QOL via a timely and more accurate clinical decision support at the point of care. Its Artificial Intelligence (AI) and analytics engine, running both at the cloud and at the mobile edge, can determine accurately which factors affect the oncological patients' QOL the most, during and after their treatment. https://cordis.europa.eu/project/id/875329	EU funded ongoing project aimed at using AI and big data to support the quality of life of cancer patients, particularly middle aged or older, during and after their treatment. The solutions being developed also aims at helping also caregivers and the healthcare professionals to understand precisely the factors most affecting patients' QoL and make better decisions on treatment and rehabilitation. Relevant to FAITH since it targets the same population, for related aims (improving QoL) and intends to use also AI.
ONCORELIEF	AI, cancer, quality of life, big data, smartphone, app	A digital guardian angel enhancing cancer patient's wellbeing and health status improvement following treatment. ONCORELIEF is a 36-month action to skilfully and methodologically overcome technical challenges, by introducing new approaches that will allow the utilization of big datasets in order to develop a user-centered AI System to facilitate the integration of QoL assessment instruments through the use of PROMs and PREMs in order to improve post-treatment health status, increase the wellbeing, and follow-up care of cancer patients. This will be achieved through an intuitive smart digital assistant (Guardian Angel), able to provide personalized support in post-treatment activities and tasks, suggest actions regarding the patients' overall health-status, improved wellbeing and active health-care and ultimately maintain him/her engaged on a wellness journey that will safeguard his/her health over the foreseeable prolonged post-cancer treatment period. https://cordis.europa.eu/project/id/875392	EU funded ongoing project that aims to use ai and big data to improve quality of life of cancer survivors. Quite relevant to FAITH given the target population and the similar aims, and also for the envisioned digital guardian angel app, which is clearly something similar to what FAITH wants to develop.
ASCAPE	AI, cancer, app, platform, privacy, support, survivor	Artificial intelligence Supporting CAncer Patients across Europe. The main objective of ASCAPE is to take advantage of the recent ICT advances in Big Data, Artificial Intelligence and Machine Learning to support cancer patients' quality of life and health status. To achieve its objective, ASCAPE will create an open AI infrastructure that will enable health stakeholders (hospitals, research institutions, companies, etc.) to deploy and execute its AI algorithms locally on their private data. Any new knowledge produced by this process will be sent back to the open AI infrastructure. This way the	EU funded ongoing project aimed at improving the care of cancer patients and survivors using ai and big data, while paying attention to privacy. Quite in line and relevant to FAITH for the target population and the means/solutions envisioned to support patients, as well as for the focus on privacy.

		knowledge will be shared among everyone while the medical data will still remain private. The services to be designed, piloted and deployed inside this project will include intelligent interventions for physiological and psychological support, improved patient and family counselling and guidance, early diagnosis and forecasts of ill-health, identification of disease trajectories and relapse, improved health literacy etc. ASCAPE will focus the training of the AI in two types of cancer, breast and prostate. This way, it will achieve sufficient coverage across genders as well as age groups, hence facilitating its ongoing improvements and applicability towards any type of cancer in the future. https://cordis.europa.eu/project/id/875351	
CLARIFY	AI, cancer, app, platform, wearable, big data, study, survivor, library	Cancer Long Survivors Artificial Intelligence Follow Up. This proposal aims at identifying cancer survivors from three prevalent types of cancer, including breast, lung and lymphomas. The patient data will be collected from different Spanish hospitals and the selection will be based on ongoing health and supportive care needs of the particular patient types. We will determine the personalised factors that predict poor health status after specific oncological treatments. For this aim, Big Data and Artificial Intelligence techniques will be used to integrate all available patient´s information with publicly available relevant biomedical databases as well as information from wearable devices used after the treatment. To predict patient-specific risk of developing secondary effects and toxicities of their cancer treatments, we will build novel models based on statistical relational learning and explainable AI techniques on top of the integrated knowledge graphs. CLARIFY proposes to integrate and analyse large volumes of heterogenous multivariate data to facilitate early discovery of risk factors that may deteriorate a patient condition after the end of oncological treatment. https://cordis.europa.eu/project/id/875160	EU funded ongoing project aimed at improving the care of cancer survivors using ai to predict poor health status. Relevant for FAITH given the target population and the use of ai.
CAPABLE	AI, cancer, survivor, coaching, support, wearable, emotions, home, big data, smartphone, library	CAncer PAtients Better Life Experience. After the primary intervention, most of cancer patients are managed at home, facing long-term treatments or sequelae, making the disease comparable to a chronic condition. Despite their benefit, strong therapeutic regimens often cause toxicity, severely impairing quality of life. This may decrease adherence to	EU funded ongoing project aimed at developing an ai-powered coaching system for cancer patients to help them and their caregivers meet the disease and treatment-related emotional, social and

		treatment, thus compromising therapeutic efficacy. Also due to age-related multimorbidity, patients and their caregivers develop emotional, educational and social needs. CAPABLE will develop a cancer patient coaching system with the objective of facing these needs/issues. The time is right to fully exploit Artificial Intelligence (AI) and Big Data potentialities for cancer care and bring them to patients' home. CAPABLE will rely on predictive models based on both retrospective and prospective data (clinical data, data from unobtrusive environmental and wearable sensors, data from social media and questionnaires). Models will be integrated with existing clinical practice guidelines and made available to oncologists. Thanks to the mobile coaching system for patients, CAPABLE will allow identifying unexpected needs, and providing patient-specific decision support. This feature, together with the chance of discovering unknown adverse effects of new treatments, makes CAPABLE more than a personalised tool for improving life quality, an advance for the whole research community. https://cordis.europa.eu/project/id/875052	educational needs and improve quality of life. Relevant to FAITH given the target population, and the intended use of AI to power a smartphone app to collect data and provide coaching.
QUALITOP	ai, cancer, survival, monitoring, quality of life, smartphone, big data, app, platform	Monitoring multidimensional aspects of QUAlity of Life after cancer ImmunoTherapy - an Open smart digital Platform for personalized prevention and patient management. Project QUALITOP aims at developing a European immunotherapy-specific open Smart Digital Platform and using big data analysis, artificial intelligence, and simulation modelling approaches. This will enable collecting and aggregating efficiently real-world data to monitor health status and QoL of cancer patients given immunotherapy.	EU funded ongoing project with a focus on QoL for post cancer patience's and usage of AI models to analyse diverse source of data
PERSIST	AI, cancer, big data, survivor, app, sensor, cross-modal, study, platform	Patients-centered SurvivorShIp care plan after Cancer treatments based on Big Data and Artificial Intelligence technologies. PERSIST aims at developing an open and interoperable ecosystem to improve the care of cancer survivors. The ecosystem proposed consists of a Big Data platform to be built on top of an open infrastructure from one of the partners and a mHealth application for patients. The main building blocks to be	EU funded ongoing project aimed at improving the care of cancer survivors using ai and big data. It is quite relevant to FAITH in that it targets the same population (post-cancer patient), aims at improving their health and wellbeing and

		developed are a multimodal sensing network running on a smart phone that will collect relevant data regarding the wellbeing of the patient; predictive models from anonymised health data from thousands of breast and colorectal patients; and modules essential for the development of a decision support system, which will employ the predictive models mentioned. Furthermore, PREDICT will contribute to establish evidence on the use of liquid biopsy techniques to the follow-up of cancer patients treated with curative purposes. A pilot study involving 160 patients and 32 health care professionals will be decisive to establish a co-creation methodology ranging from the earlies phases of the project throughout its conclusion https://cordis.europa.eu/project/id/875406	envision the use of a smartphone application collecting data on patients' health from sensor to make predictions. Data should be anonymised. A difference from FAITH is that depression is not explicitly considered.
Project Baseline	mental health	Project Baseline is an initiative to make it easy and engaging for people like you to contribute to the map of human health and participate in clinical research. Together with researchers, clinicians, engineers, designers, advocates, and volunteers, we're collaborating to build the next generation of healthcare tools and services https://www.projectbaseline.com/	This project has similar goals to those FAITH is pursuing. The main difference is the target audience, general public while FAITH is for post cancer treatment which motivates a different kind of assessment with a higher granularity.

5 DATA ASSETS

It is clear that FAITH leverages techniques (Machine Learning even in its Federated Learning approach, Analytics, etc) that require the usage of meaningful volumes of data in order to produce good results for the problem. For this reason, data assets are of critical importance in the project. The challenge tackled by FAITH requires, however, a very specific segment of data and needs to be tailored to real users. Publicly available datasets used in literatures can be useful in the initial phases of the algorithms' design and for specific modules.

Cummins, in [3] provides a comprehensive overview of the datasets used for detecting depressed and suicidal traits in speech. The table is reported below.

Summary of depressed and suicidal speech databases which have had results published on them in the last 10 years. Abbreviations: *DPRD* – Depressed, *SCDL* – Suicidal, *NTRL* – Neutral, not depressed or suicidal, *M* – Number of males, *F* – Number of Females *DSM* – Diagnostic and Statistical Manual of Mental Disorders, *HAMD* – Hamilton Rating Scale for Depression, *BDI* – Beck Depression Inventory, *QIDS* – Quick Inventory of Depressive Symptomology, *PHQ-9* – Patient Health Questionnaire, *C-SSRS* – Columbia Suicide Severity Rating Scale, *SIQ-Jr version* – Suicidal Ideation Questionnaire – Junior. *Note:* where DSM is present as a clinical score all depressed patients in corpus meet criteria for Major Depressive Disorder.

1st Published (Name)	Subjects	Clinical scores	Vocal exercises	Read speech	Free response or interview	Free speech	Additional notes	Other references
France et al. (2000) Vanderbilt II Study	115: 59 DPRD (21M, 38F) 22 SCDL (all M) 34 NTRL (24M, 10F)	DSM-IV BDI (DPRS = BDI > 20)			√	√	*Recorded therapy sessions or suicide notes* Mean file length: *2 min 30 s* Age range: 25–65 Medications Present: *Imipramine-hydrochloride*	*Similar corpus used in:* Ozdas et al. (2004a,b, 2000) and Hashim et al. (2012)
Moore et al. (2004)	33: 15 DPRD (6M, 9F) 18 NTRL (9M, 9F)	DSM-IV		√			Utterances per speaker: 65 Mean file length: *3 min* Age range: 19-57	Moore et al. (2008) *Similar corpus used in:* Moore et al. (2003)
Yingthawornsuk et al. (2006)	32(all M): 10 SCDL 13 DPRD 9 Remitted Patients	BDI (DPRD = BDI > 20)		√	√		Mean file length: *Free Response – 8 min* *Read Speech – 2 min* Age range: 25–65	*Similar corpus used in:* Keskinpala et al. (2007), Landau et al. (2007), Yingthawornsuk et al. (2007), and Hashim et al. (2012)
Mundt et al. (2007)	35: DPRD (15M, 20F)	HAMD Mean: 14.9 ± 6.3 Range: 3–27 QIDS Mean: 12.4 ± 6.1 Range: 0–26	√	√	√		Mean age: 41.8 Medications: *Range present*	Sturim et al. (2011), Trevino et al. (2011), Quatieri and Malyska (2012), Cummins et al. (2013a,b), and Helfer et al. (2013)
Cohn et al. (2009)	57: DPRD (24M, 34F)	DSM-IV HAMD (HAMD ⩾ 5)			√		Min. vocalisation per speaker: *100 s* Mean age: 39.7 Age range: 19–65 Medications: *SSRI's present*	*Extended version:* Yang et al. (2012)
Low et al. (2009)	139: 68 DPRD (49F, 19M) 71 NTRL (71M, 44F)	N/A			√	√	Recordings per subject: 3 Mean file length: *20 min* Age range: 12–19	Memon et al. (2009), Low et al. (2011, 2010), and Ooi et al. (2013, 2012)
Alghowinem et al. (2012)	80: 40 DPRD 40 NTRL	DSM-IV		√	√		Mean file length: *40 min*	Alghowinem et al. (2013a,b), and Cummins et al. (2013b) *Subset published in:* Cummins et al. (2011)
Mundt et al. (2012)	165: All DPRD (61M, 104F)	DSM-IV HAMD QIDS	√	√	√		Age range: 21–75 Mean age: 37.8 Medications: *Sertraline*	None
Scherer et al. (2013a)	60: 30 SCDL 30 NTRL	C-SSRS SIQ-Jr version			√		Age range: 13–17	None
Scherer et al. (2013c) *Distress Assessment Interview Corpus*	110: 29%: DPRD 32%: PSTD 62%: Anxiety	PHQ-9 (DPRD = PHQ-9 > 10)			√		Data per participant: *30–60 min* Age range: 18–65	Scherer et al. (2013b,d)

N. Cummins et al. / Speech Communication 71 (2015) 10–49

Valstar et al. (2013) *Audio-Visual Depressive Language Corpus (AViD Corpus)*	292: *AVEC 2013:* 150 files each containing a range of mix of vocal exercises, free and read speech tasks *AVEC 2014:* 150 files each containing a read speech passage (Die Sonne und der Wind) and an answer to a free response question. *Note* AVEC 2014 is a shortened (file length) version of AVEC 2013. 5 files were replaced in 2014 due to unsuitable data	DBI *Mean AVEC 2013 Training Set: 15.1 ± 12.3 Development Set: 14.8 ± 11.8* *Mean AVEC 2014 Training Set: 15.0 ± 12.3 Development Set: 15.6 ± 12.0*	√	√	√		*For AViD-Corpus:* German Language Mean file length: *25 min* Age range: 18–63 Mean age: *31.5 ± 12.3*	*AVEC 2013 Papers:* Cummins et al. (2014a,b, 2013c), Kaya and Salah (2014), Kaya et al. (2014b), and Williamson et al. (2013) *AVEC 2014 Papers:* Valstar et al. (2014), Gupta et al. (2014), Kaya et al. (2014a), Mitra et al. (2014), Pérez et al. (2014), Senoussaoui et al. (2014), Sidorov and Minker (2014), and Williamson et al. (2014). *Similar corpus used in:* (Hönig et al., 2014) – 1122 recordings taken from 219 speakers in AVDL Corpus

Table 4 – Summary of depressed and suicidal speech databases from Cummins [3]

A set of datasets involving psychosocial and medical data instead is available at the Banque Signature website [3]. The website hosts a dataset that maps clinical signs (Psychosis, Depression, Anxiety etc), addictions, sleep quality, social behaviors and experiences, demographic and medical data are collected through surveys from a mobile application.

In general, the availability of this kind of data seems to be very low. To kick-start the initial training of the models, in the absence of existing, usable datasets FAITH leverages the domain expertise of the hospital partners, and state-of-the-art techniques such as Active Learning (a technique that relies on collaboration between machines and humans to label smartly) and Synthetic Dataset generation.

Active Learning: Active learning makes it possible to build applications using a small set of labelled data and enables enterprises to leverage their large pools of unlabeled data [13]. The fundamental belief behind the concept is that a Machine Learning algorithm could potentially achieve a better accuracy while using fewer training labels if it were allowed to choose the data it wants to learn from. Such an algorithm is referred to as an active learner. Active learners are allowed to dynamically pose queries during the training process, usually in the form of unlabeled data instances to be labelled by what is called an oracle, usually a human annotator. As such, active learning is one of the most powerful examples of the success of the Human-in-the-Loop paradigm [14].

Synthetic Datasets: The vast majority of AI success stories have come as a result of training models with massive datasets, e.g. one of Facebook's latest Detectron models for object detection was trained on 3.5 billion images from Instagram [15]. There are many potential successes, however, that remain unrealised due to a lack of training data, whether for reasons of privacy, or simply scarcity. Some researchers have solved this problem creatively by employing what are known as Synthetic Datasets– virtually constructed datasets designed to be used in absence of real-world data in the machine learning process.

These techniques will produce an initial curated dataset will allow us to train a model that can be deployed, and subsequently retrained with real user data. Once the model(s) have been deployed it is crucial to monitor their performance over time. At the NVIDIA GPU Technology Conference 2018, Jensen Huang, NVIDIA President and CEO, put forward the PLASTER framework to contextualize the key challenges delivering AI-based services. PLASTER outlines seven aspects of an AI service that should be measured: **P**rogrammability, **L**atency, **A**ccuracy, **S**ize of Model, **T**hroughput, **E**nergy Efficiency, **R**ate of Learning.

[3] https://www.banquesignature.ca/en/les-donnees-2/psychosociales-et-medicales/

When talking about data in the context of FAITH it is important to recall the key questions posed by the project i.e. “does there exist a set of variables that can be captured via a smartphone, that can accurately predict the onset of depression and/or changes to quality-of-life”. Until we run user trials and begin monitoring the participants we won’t know the answer to this, so we won’t know what the appropriate dataset will be. Here is where synthetic data generation can be incredibly useful, we can use the expertise of the medical partners to envisage what this dataset might look like, and at least create it to be certain the technical performance of the FAITH platform is running as it should, i.e. processing of data, deployment of federated models etc.

As the trials progress our aim would then be to deploy updated models to take the newly discovered dataset as input.

6 DASHBOARD OF THE FAITH RESOURCES

FAITH tackles complex and fast changing problems. As an example, during the first months of the project many technologies improvements have been introduced for supporting federated learning in the most important libraries for building AI modules. Furthermore, we deal with multidisciplinary goals and the wide scope of the project makes difficult to be sufficiently aware of the related and potential useful results with a single review of the literature. As the project matures, new results and technologies will come and to support this dynamicity, we built an easy to update and explore online dashboard including and organizing all the collected material. This chapter describes such dashboard.

6.1 Dashboard Technical Overview

The dashboard is available at the following address https://dashboard.h2020-faith.eu/
It is fed by a simple excel file containing all the resources collected by the consortium partner during the task T2.1 organised conveniently to be presented in the visualization. The dashboard is built on top of the following technologies

- R as main programming language https://www.r-project.org/about.html
- Shiny: an R package that makes it easy to build interactive web apps straight from R https://shiny.rstudio.com/
- Shiny-Server: an application server that allows to deploy web applications built with shiny https://rstudio.com/products/shiny/shiny-server/
- Plotly: a charting library for R, Python and Javascript that allows building rich and interactive data visualizations https://plotly.com/r/

Each resource is associated with a set of topics (e.g. AI, Federated Learning, Detection of Depression, Cancer, etc) and it belongs to one Resource Type, namely it can be a Scientific Paper, Research Project, Software Library, Dataset, Internet Article, Internet Resource, or other kind of resource not categorized.

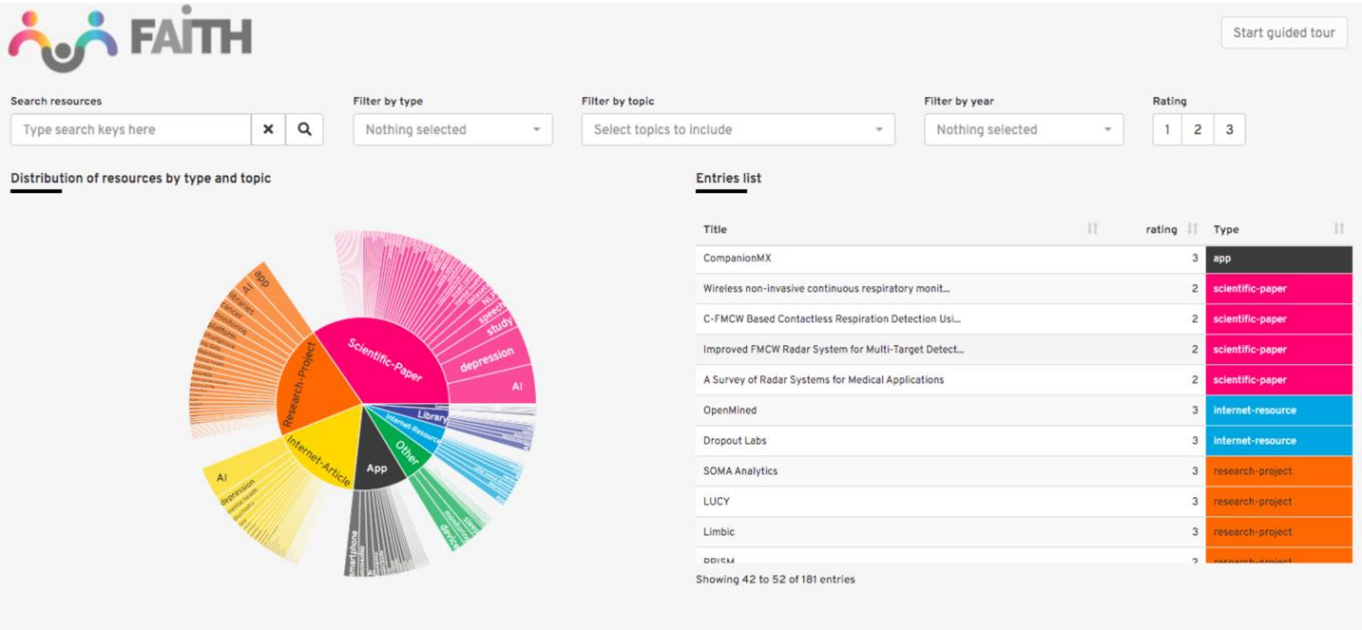


Figure 1 - Dashboard main view

6.2 Dashboard main features

Figure 1 shows the dashboard main view: the most important part of the view is represented by the sunburst chart placed at the left of the page. The chart allows to present the distribution of the type of resources in the inner part of the circle, and for each type, what topics are included. For example, Figure 2 shows that for the scientific paper type there are 33 resources included in the dataset.

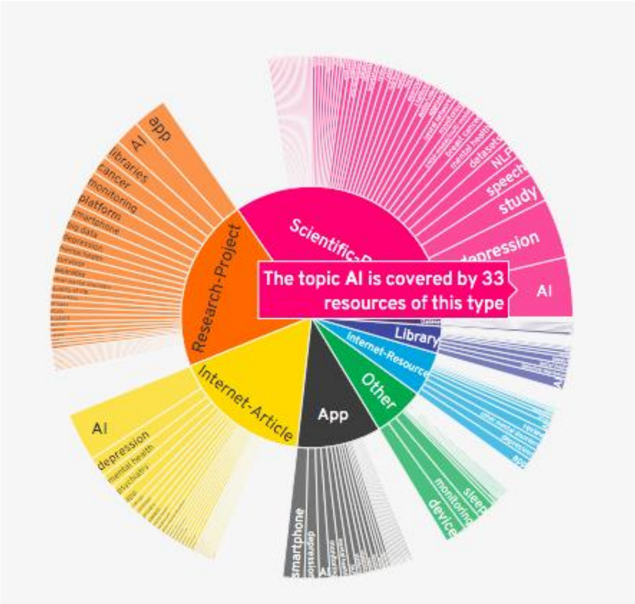


Figure 2 - AI scientific papers example

The chart not only covers a visualization function, but also allows the selection. Clicking on a resource type or on a topic, directly selects the related portion of the resources that are presented in the list at the right of the page.

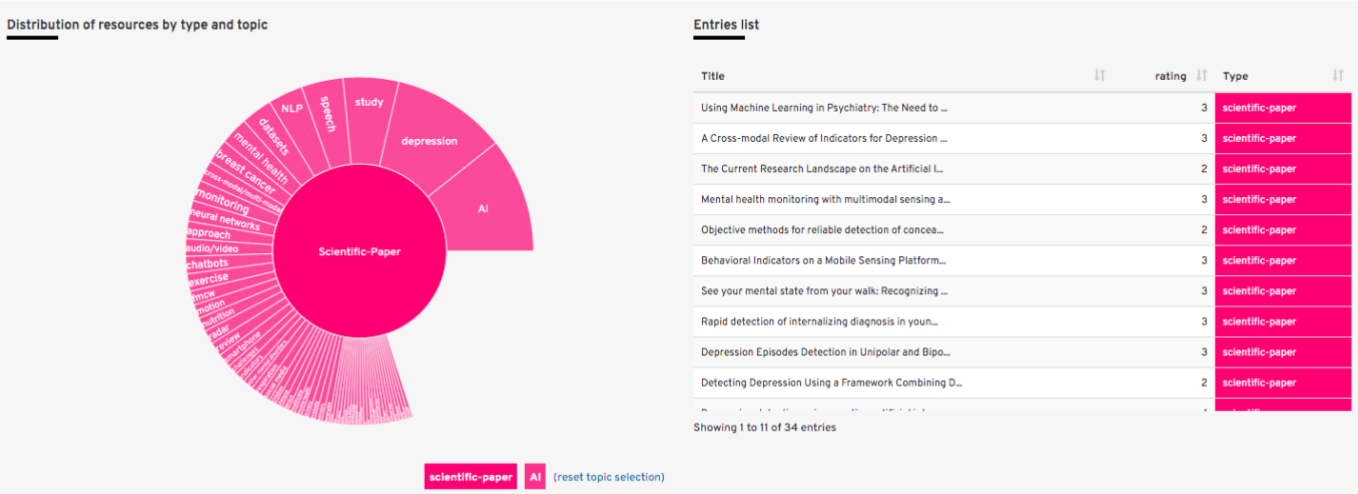


Figure 3 - Selection of topic/resource type

When an entry is selected from the list, a card showing all the information about the resource is presented at the bottom of the page. Information include a description of the resource, its relevance for FAITH, the rating of relevance assigned by the consortium, the related topics and a link to access the resource.

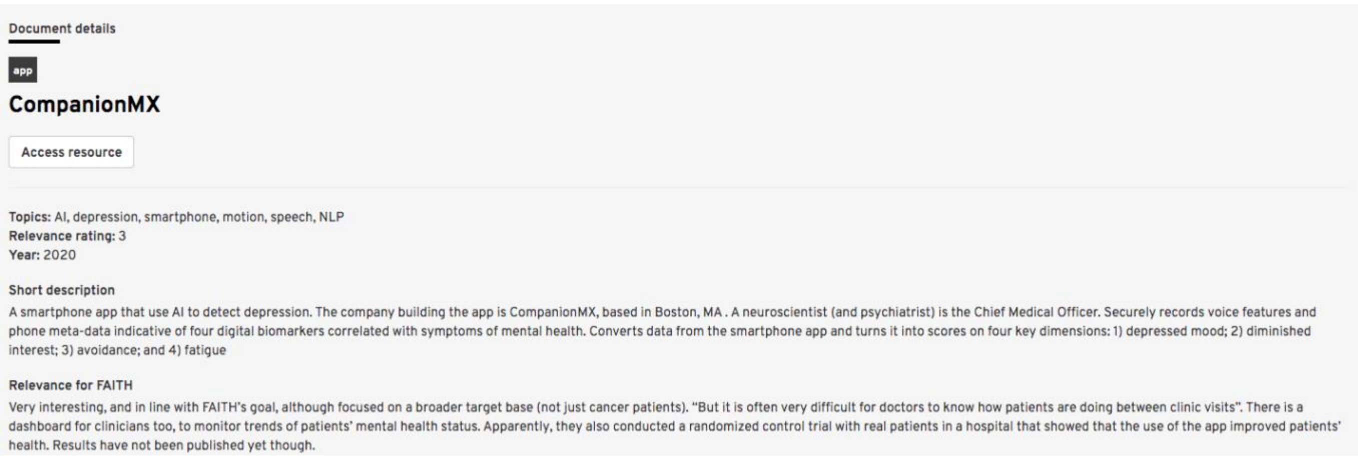


Figure 4 - Info Card of the resource "CompanionMX"

Finally, the dashboard allows the filtering of the resources based on parameters placed on top of the page. Users can search free text all the fields of the resources, filter by type, topics, year and rating.

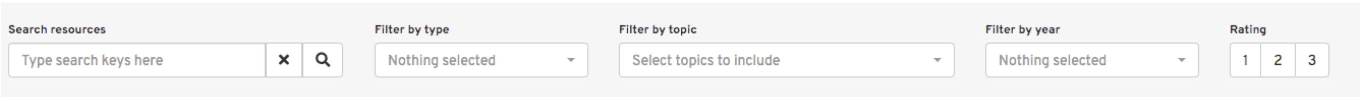
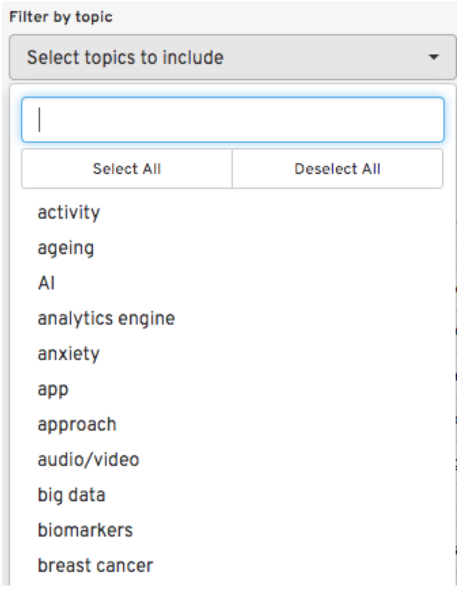
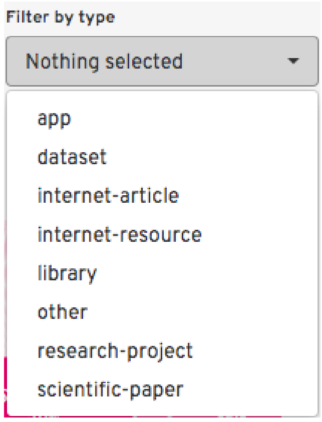


Figure 5 - Sets of filters available in the dashboard





7 CONCLUSIONS

This document presented a state of the art of the main topics touched by the FAITH concept and a description of the initial data assets that may be exploited to develop our models. Resources in the form of scientific papers, information on related research projects, technologies, devices and existing products were collected by the entire consortium in order to cover all the important points. In FAITH, we will leverage the existing technologies and approaches, in particular the ones related to federated learning and artificial intelligence for detecting mental health conditions. In doing so, the project will still preserve a high degree of novelty by tackling privacy issues with the federated learning architectures and focusing on conditions related to cancer survivorship.

Among the scientific challenges, the detection of depression with the support of machine learning models appears to be the one in which FAITH can contribute the most: there is an overall agreement on the need to use multiple indicators to approach the problem, but selecting the correct ones for the specific individuals and situations is still an open topic of discussion. Related research projects in the EU are focusing, or have focused, on similar topics such as improving QoL of cancer survivors and patients suffering with various diseases. There is a general awareness of the privacy issue when applying AI models to these situations and while many attempts are in place and directed towards an augmented security of the data, there are very few works aiming at preventing the problem as it happens using the federated approach.

Data availability might represent a weak spot of the artificial intelligence world, as it is for the FAITH concept, but this can be initially mitigated with the usage of synthetic data, and intermediate results during the trials will provide more information regarding the real data needs of our models. Furthermore, identifying the right data for the challenge is one of the objectives of the project.

Finally, due to the changes and improvements that are likely to occur in these fields, we adopted an incremental approach for collecting and reviewing assets and results. This is translated in the usage of the live dashboard that will be updated and will work as main asset dictionary for the consortium for the whole project.

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