# Chapter 10
# Artificial Intelligence in Digital Mental Health

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## ABSTRACT

*The prevention of diseases considered a scourge of our society, as for example mental illness, particularly anxiety disorders and depressive states, is a primary and urgent goal today and a priority axis of the EU. Mental illness includes many clinical conditions associated with several changes that include limitations related with social interaction or several tasks such as sleeping through the night, doing homework, making friends, thinking capacity and reality understanding, deficits in communication skills, and difficulties in developing appropriate emotional and behavioural response. Artificial intelligence has gained a prominent role in the management and delivery of healthcare. There is a growth in mobile devices applied to health with high mobility, connectivity, and processing capacity. This chapter provides an analysis of the actual trends regarding the main problems that can be dealt with using AI in mental healthcare and the corresponding main techniques used to deal with these problems. Additionally, some case studies for using AI for mental health care are described.*

DOI: 10.4018/978-1-7998-8634-1.ch010

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## INTRODUCTION

Since the primordial days of Artificial Intelligence (AI), many applications in the medical area have been developed. Initially, Knowledge-Based Systems, and in particular, Expert Systems were the first AI approaches to develop applications in the field of medicine. However, the current advances in computational capacity, data acquisition and machine learning techniques have contributed to a growing interest in AI.

One of the difficulties for doctors that arise during the diagnostic process is related to the fact that interactions with the patient only offer an instantaneous image of an individual's mental state, although mental state disorders can be dynamic, changing over time. As the availability of medical teams is limited, psychiatric assessment of patients based on the observation of their mental state can only be carried out for short periods. AI can provide alternative methods, such as audio and video analysis, bringing greater objectivity and may present better predictive behaviour.

AI may be combined with smartphone applications to increase monitoring coverture, during a significative period of the patient's day. These applications can actively query users about their state of mind, sleeping periods and other relevant habits. The behaviour of patients can be tracked by these apps, such as smartphone activity, the variation of the voice, speaking rate, and voice quality. These tracked behaviours can be used as predictors of symptoms of depression and other mental disorders.

Another aspect related to monitoring is the fulfilment of drug prescriptions. This is a problem that accompanies all chronic patients and is of particular importance in mental health problems. There are several examples of applications for smartphones that aim to assist the patient in fulfilling drugs prescriptions, generating alerts about the need for taking medications. The application of machine learning techniques in this context can allow these applications to have the ability to adapt to the patient, thus improving their recommendation capabilities, always with the aim of improving the patient's adherence to medication.

AI can also have an important role in the prevention of episodes of mental disorder. Machine Learning can be effectively used to identify words and emojis that can signal a person at higher risk of suicide ideation or self-harm. Artificial intelligence can allow existing treatments to be provided through new approaches, which can increase availability and effectiveness. Virtual therapists can be powered with AI tools to avoid patients getting embarrassed to share problems with a therapist with whom they interact for the first time.

Recent improvements in conversational systems, allowed chatbots to mimic normal conversational style to increase adherence to treatments and decrease both depression and anxiety. However, these systems are still in a preliminary stage of research but already reveals great potential for improvement.

AI may contribute to providing more time for medical staff to interact with patients and improving the quality of care. Natural Language Processing (NLP) offers a set of techniques allowing the implementation of applications that can be used to save time for psychiatrists. These professionals need an appreciable time to read previous notes that allow them to build the patient's accurate history. For example, NLP techniques can be applied to get a summary of the most relevant data from a patient's health records, providing that way with a succinct summary at the beginning of a clinical visit.

The first National Mental Health Epidemiological Study, carried out as part of the World Mental Health Survey Initiative, ranks Portugal as the second European Union country with the highest prevalence of psychiatric disorders (22.9%), only surpassed by Northern Ireland (23.1%). In this study, anxiety disorders representing the group of mental illnesses with the highest prevalence in our country (16.5%) and the second highest impact in terms of disability adjusted years (daily of 1.8%), with a tendency to

grow in the coming years (Direção Geral de Saúde, 2013), (Direção Geral de Saúde, 2016), (Direção Geral de Saúde, 2017).

This chapter will provide a in analysis of the actual trends regarding the main problems that can be dealt with AI in mental healthcare, and the corresponding main techniques used to deal with these problems. Additionally, some case studies for using AI for Mental Health Care will be described.

## AI Applied to Mental Healthcare

A new technology may face several challenges every time it enters healthcare. Common setbacks of AI in healthcare include a lack of data exchange, regulatory compliance requirements and patient and provider adoption. AI has come across all these issues, narrowing down the areas in which it can succeed.

The most popular use of artificial intelligence in healthcare is in IBM's smart cloud, where Watson lives (IBM, 2016). The Watson platform has been used in several disciplines within healthcare including with payers, oncology, and patient risk assessment.

There are a few other applications within healthcare where AI can deliver incredible value, but healthcare executives must evaluate and see if they can adopt some or all of them to begin their journey in the AI space. Examples of areas where AI is gaining relevance include the personal health virtual assistants, personal life coach, and healthcare bots.

AI has great potential for the diagnosis and understanding of mental disorders. AI techniques can offer the ability to develop better prevention tools and formulate models to determine a predisposition or risk of developing mental illness.

## Personal Assistant and User Modelling

A Personal Assistant (PA) is a tool that can contribute to improving independent living but, many times, poor and rudimentary traditional PA approaches devotes low attention to key issues such as suggesting changes in people behaviours (individual and collective), or to support the prevention of mental disorders, which often are inhibiting factors of daily activities. The use of this kind of technology can improve the quality of life and support more independent living.

In PA, the User Model (UM) has increased relevance. The UM allows changing several aspects of the system, in reply to certain characteristics (given or inferred) of the user (Martins et al., 2008).

Contextual PA can infer what the user said before, when/where/how they said matters and should influence how the conversation goes and how the recommendations are given. The use of this kind of technology can improve quality of live and support more independent live.

In (Centry et al., 2008) is presented a study to examine the efficacy of personal assistants as cognitive aids in a sample of individuals with severe traumatic brain injury. Behavioural memory deficit is one of the most often-cited complaints among individuals with acquired brain injury.

A user model is composed by a set of characteristics that adjust the content, presentation, and navigation to each user. These characteristics can be domain-dependent and domain-independent and are related with beliefs about the user, which include preferences, knowledge, and attributes, or are an explicit representation of properties of individual users and user classes (Martins et al., 2008).

Domain dependent data is related with system responses tailored according to the domain knowledge of a user (Durrani, 1997) (Martins et al., 2008). For this, it is necessary to perceive user current state and knowledge regarding concepts and relations inherent to the domain, predict how the user will interpret

system responses, understand the many different goals, and plans of each user, predict and respond to different mistakes while the user is using the system and identify the most adequate way to present information to each user. Different methods can be used to measure user knowledge and expertise regarding the domain: Direct Dialogue and Indirect Acquisition.

### Direct Dialogue

This type of interaction is performed directly with the user to assess his/her expertise regarding the domain. For this, the system should incorporate features to allow users to input and share their knowledge (for example, using questionnaires or forms) and mechanisms to process the inserted data to correctly measure user knowledge regarding the domain.

### Indirect Acquisition

Indirect acquisition method allows the system to assess user knowledge indirectly according to how the user performs different actions. Depending on this assessment the user knowledge regarding the domain is classified in different levels which in turn are updated over time as the user works with the system.

Domain independent data is not related with user expertise regarding the domain but to his/her cognitive abilities which indicates how the user perceives, thinks, remembers, behaves, and solves different problems (Durrani, 1997). In other words, domain-independent knowledge corresponds to the phycological characteristics of the user. There are many different psychological models and tests that can be used to assess user personality such as the Myer-Briggs Type Indicator, the Eysenck's Pen Model and the Big Five Model.

### Myer-Briggs Type Indicator

Myer-Brigg Type Indicator model (Myers, 1962) is a model used to identify personal characteristics and preferences. This model considers four different areas of personality based on the Carl Jung's Psychological Types (Jung, 2016) and which are perception, judgment, extraversion, and orientation. These four areas combined result in sixteen different types and the scores on each dimension represent the strength of each dimension (Figure 1).

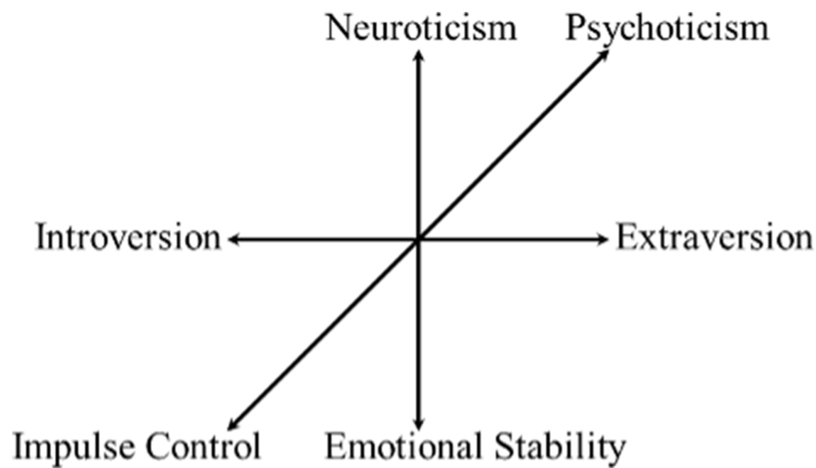
### Eysenck's Pen Model

In 1950 (Eysenck, 1950), Eysenck proposed the PEN model (Figure 2) using three dimensions to describe different personalities. These dimensions are extraversion-introversion; Neuroticism versus Emotional Stability; and psychoticism versus impulse control. According to Eysenck, individuals with high levels of extraversion are more social, talkative, and outgoing, while individuals with high levels of introversion are more quiet, shy and less social. Individuals with high levels of neuroticism experience more stress and anxiety, while individuals with low levels of neuroticism experience more stable emotional levels. Individuals with high levels of psychoticism are more likely to show impulsive, irresponsible, and miscalculated behaviour while individuals with low levels of psychoticism tend to be more controlled and organized.

*Figure 1. Myer-Briggs type indicator*

| | | | |
|---|---|---|---|
| ISTJ Responsible Executors | ISFJ Dedicated Stewards | INFJ Insightful Motivators | INTJ Visionary Strategists |
| ISTP Nimble Pragmatics | ISFP Practical Custodians | INFP Inspired Crusaders | INTP Expansive Analyzers |
| ESTP Dynamic Mavericks | ESFP Enthusiastic Improvisors | ENFP Impassioned Catalysts | ENTP Innovative Explorers |
| ESTJ Efficient Drivers | ESFJ Committed Builders | ENFJ Engaging Mobilizers | ENTJ Strategic Directors |

*Figure 2. Eysenck's pen model*



## The Big Five Model

The Big Five Model (Figure 3), also known as the OCEAN model has been proposed and developed over the last century by different researchers such as Fisk, 1949 and Goldberg, 1990. This model considers the existence of five main traits of personality which are extraversion, agreeableness, openness, conscientiousness, and neuroticism.

**Openness:** Trait associated to characteristics such as imagination and insight. People who have high openness tend to have a broad range of different interests about the world and other people and are willing to learn new things and enjoy new experiences.

**Conscientiousness:** Trait associated to characteristics such as thoughtfulness, good impulse control, and goal-directed behaviour. People who have high conscientiousness tend to be organized and mindful of details.

**Extraversion:** Trait associated to characteristics such as excitability, sociability, talkativeness, assertiveness, and emotional expressiveness. People who have high extraversion tend to be outgoing and value social interactions.

**Agreeableness:** Trait associated to characteristics such as trust, altruism, kindness, affection, and other prosocial behaviours. People who have high agreeableness tend to value cooperation.

**Neuroticism:** Trait associated to characteristics such as sadness, moodiness, and emotional instability. People who have high neuroticism tend to experience mood swings, anxiety, irritability, and sadness.

## Techniques for User Modelling

After identifying the data related to each user characteristics, it is then possible to define the algorithms that will process this data and in turn affect the computational environment. These algorithms are mainly defined using statistical and non-statistical techniques.

### 1. Statistical Techniques

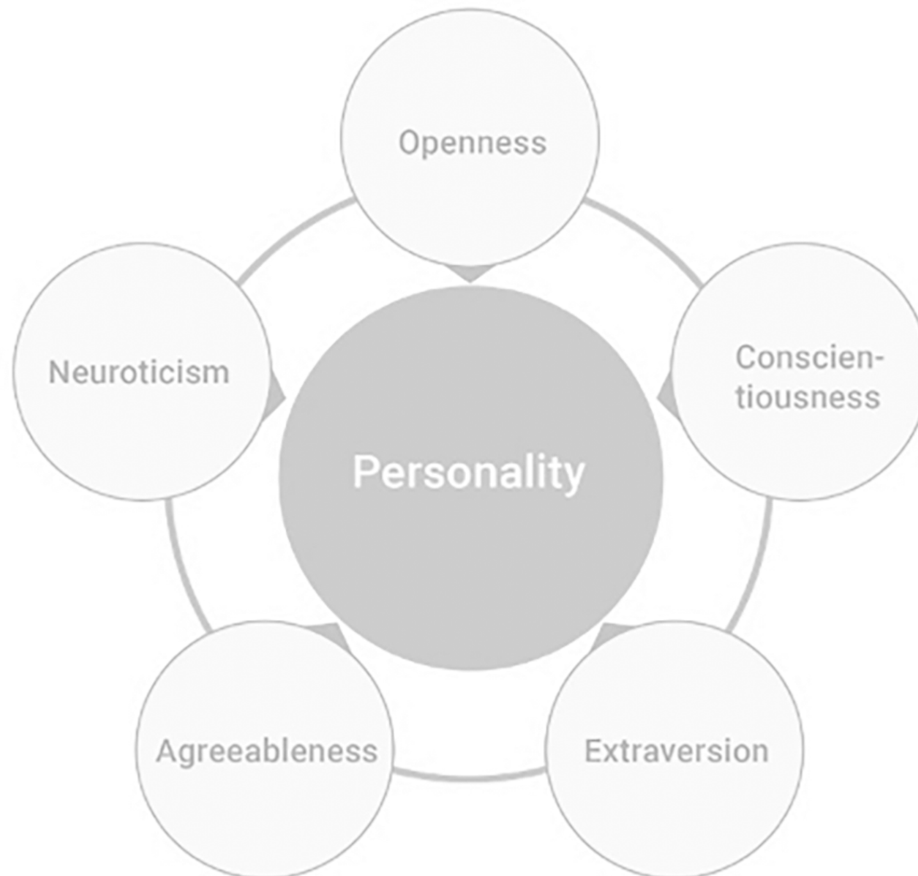
### a. Linear Modelling.

Linear Modelling is a technique which takes the weighted sum of known values and predicts the value of an unknown quantity (Zukerman & Albrecht, 2001). These models are usually very inexpensive and easy to learn and understand. Furthermore, these models can be also extended and generalized without much effort. Two examples could be using a linear model to predict user's ratings of different activities suggested by the system or using linear model to assess the association between total cholesterol and body mass index.

#### *Beta Distribution*

The Beta Distribution is a predictive model which considers the number of correct predictions and the number of incorrect predictions and then generates both and estimate and a confidence level (Orwant, 1996). It is easy and cheap to calculate since it only requires two numbers (the number of hits and misses) to measure both estimate and confidence level. An example could be using a Beta Distribution model

*Figure 3. Five traits of personality*




to track users' preferences by the number of likes and dislikes they provide to system for any suggested activity.

## b. Markov Model.

A Markov Model follows a structure very similar to a Linear Model and consists of a set of states, a set of probabilities which determine the likelihood of transition between these states and, for each state, a set of observation/probability pairs (Zukerman & Albrecht, 2001). For example, a Markov Model could be used to predict user most frequent actions while using the system by looking at his past performed actions.

## c. Bayesian Networks

A Bayesian Network is a directed acyclic graph where nodes denote variables and the arcs connecting nodes represent causal links from parent nodes to child nodes (Zukerman & Albrecht, 2001). Each node is associated with a conditional probability distribution which assigns a probability to each possible

value of this node for each combination of values of its parent nodes. These models are usually very flexible as they can provide a compact representation of any probability distribution, they can explicitly represent causal relations and they allow predictions regarding more than one variable (unlike many other statistical models which only considers a single variable). Examples of Bayesian Network models could be to predict the most adequate type of suggestions for a user according to the type of action being performed, or to predict error rates while the user is using the application.

### d. *Rule Induction Model*

Rule Induction Model consists of learning sets of rules that predict the class of an observation from its attributes (Zukerman & Albrecht, 2001). These models can represent rules directly or represent rules as decision trees or in terms of conditional probabilities. A rule itself is not considered a model and therefore, this type of models always considers a set of rules which collectively define a prediction model, or the knowledge base.

## 2. Non-Statistical Techniques

### a. Overlay Model

An overlay model assumes that the user's knowledge is a subset of the domain knowledge. An overlay user model can thus be thought of as a template that is "laid over" the domain knowledge base. Domain concepts can then be marked as "known" or "not known" (or with some other method, such as an evidential scheme), reflecting beliefs inferred about the user. Overlay modelling is a very attractive technique because it is easy to implement and can be very effective. An overlay model cannot account for users who organize their knowledge of the domain in a structure different from that used in the domain model, nor can it account for misconceptions users may hold about knowledge in the knowledge base (Kass et al., 1988).

The overlay model consists of (a subset of) the concepts from the underlying domain model. For each concept, the overlay model contains data that represents (an estimation of) the individual user's knowledge about or interest in this concept (or some other relationship with this concept) (Martins et al., 2008).

### b. *Perturbation Model*

The perturbation model can represent user beliefs that the overlay model cannot handle. A perturbation user model assumes that the beliefs held by the user are similar to the knowledge the system has, although the user may hold beliefs that differ from the system's in some areas. These differences in the user model can be viewed as perturbations of the knowledge in the domain knowledge base. Thus, the perturbation user model is still built with respect to the domain model but allows for some deviation in the structure of that knowledge (Kass, 1988).

Perturbation model represents learners as the subset of expert's knowledge plus their mal-knowledge (Nguyen & Do, 2009).

This method considers that the knowledge and the student aptitudes are a perturbation of the specialist knowledge, and not a subset of his knowledge (as in the previous model) (Martins et al., 2008). This method can be used to represent knowledge that is beyond the Domain Model defined by the specialist.

## 3. Knowledge Modelling

Process of creating a computer interpretable model of knowledge or standard specifications about a kind of process and/or about a kind of facility or product. The resulting knowledge model can only be computer interpretable when it is expressed in some knowledge representation language or data structure that enables the knowledge to be interpreted by software and to be stored in a database or data exchange file.

### a. Behaviour-Based Model

A very common approach to gather requirements for developing a system is to interview and observe the behaviours of users from the intended user population. System design requirements typically characterize the user as one entity with a single set of behaviours, namely expert, novice, or a composite of all the users (Bushey et al.,1999). The goal of this type of models is to develop a system that can accommodates the great diversity of the user population and improve the users' performance. For this, system users can be categorized into different groups, and then it should be described and modelled each group's behaviours, and finally, this information should be included in both design and operational processes. Users can be categorized based upon similar behavioural characteristics that are important to system interface design and use. User modelling should then describe how users within a specific user group behave in certain situations or perform certain functions.

### b. Rule-Based Model

Rule-Based Models can be automatically defined using learning algorithms to identify useful rules (also known as Rule-based Machine Learning Modelling) or can depend on expert-crafted knowledge bases to make inferences about users (traditional Rule-Based Modelling). Examples of this type of models could be using a Rule-Based Model to model user's current abilities, or to predict actions and errors performed by the user. Other examples include using a Rule-Based Model to identify irregular monitoring values captured by the application regarding current user health condition and alert the healthcare professional.

### c. Stereotypes

One of the easiest and most common techniques for building models of other people is the evocation of stereotypes. Stereotypes were first introduced in the literature related to User modelling by Elaine Rich in 1979 (Rich, 1979), and it was brought with the necessity to define a "useful mechanism for building models of individual users on the basis of a small amount of information about them". According to the author, to correctly define and use stereotypes it is necessary to collect and use two kinds of information. The first required information is related to the stereotypes themselves which includes the information of different collections of clusters of characteristics or facets. These facets depend on the domain and purpose of the system but may also include information related to the level of expertise while using the system or specific concepts and tasks dealt with by the system. These different facets will result and describe different groups of users. The second kind of information is related to the use of triggers which correspond to the occurrence of different events and that in turn will activate appropriate stereotypes. For example, if a user performs an advanced task while using the system, an "expert user" trigger could be activated.

## 4. Ontologies

Nowadays, there is a great necessity to develop systems which can reuse and share knowledge and information for all sort of areas and applications including healthcare. To support such kind of systems, new tools are being developed, also known as Ontologies. One of the most common definitions comes from Gruber which refer to ontologies as "an explicit specification of a conceptualization" (Gruber, 1993). Although it seems a very simple definition, it is widely accepted in the Artificial Intelligence domain. To sum up, an ontology describes a data model, represents concepts and relationships existing in a certain domain. These relationships should allow inferring about all different instances related to the domain. The information represented by an ontology should include individuals (or instances), classes (concepts or types of instances), attributes (concepts' properties which can be mandatory or nor) and relationships (how concepts are related with each other). Some of the most used languages to define and instantiate ontologies are the RDF and RDFS (Brickley, 2004) and OWL (McGuinness & Van Harmelen, 2004)

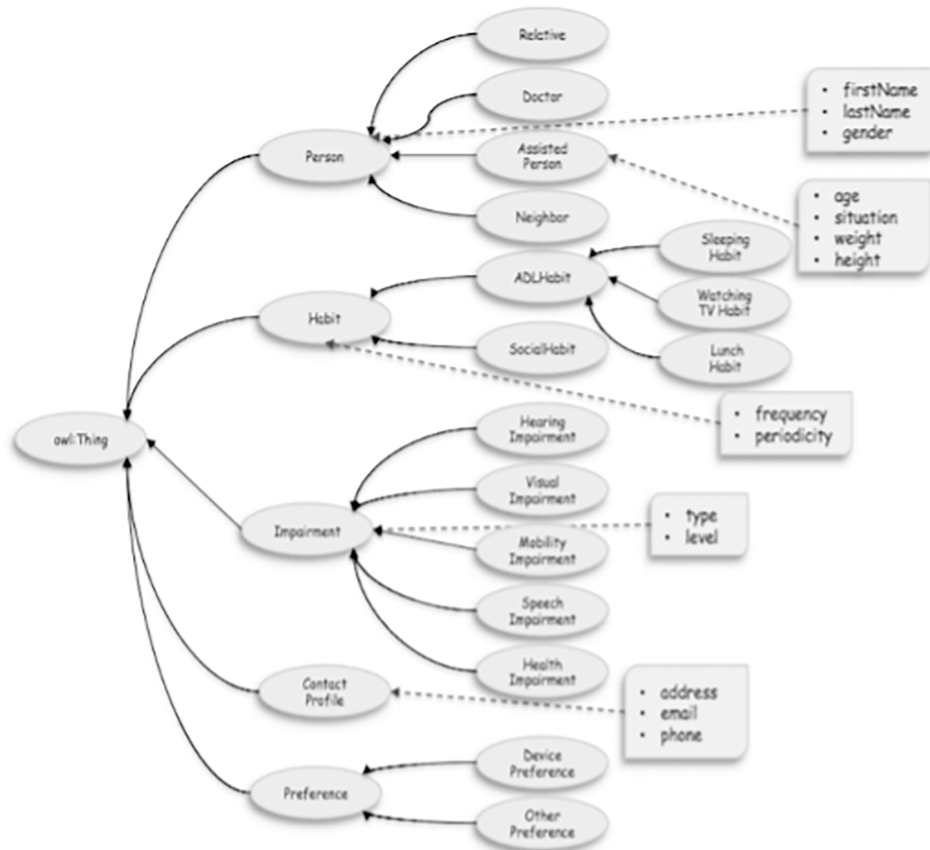
### a. User Ontologies.

A user ontology classifies all the relevant characteristics and associated partitions of users into classes with corresponding associated information. In other words, a user ontology includes all the characteristics that can describe the user as a person (Andrejko, 2007). Using sharable data structures containing user's features and preferences will enable personalized interactions with different devices for the benefit of the users (Gouardères, 2005). A user ontology can be defined using OWL description language which contains the following elements: $C$ .– a set of concepts (entities and instances in user ontology); $R$ .– the relationship between classes or instances in the user ontology. $I$ .– a set of instances and $A$ .– a set of rules and restrictions (Jiang, 2009). Several works have been proposed in the literature regarding the definition and use of user ontologies. For example, in (Zografistou, 2012) it is proposed a Person Profile Ontology model which is responsible for modelling the profile of the user using five main classes: Person (can be either the assisted person, doctor, relative, etc,), Habit (daily activities performed by the assisted person), Impairment (visual, mobility, speech and other impairments associated to the assisted person), Contact Profile (email, phone number and other mechanisms to contact the assisted person) and Preference (preferences of the assisted person such as device preferences).

In (Ni et al., 2016), it is proposed a user ontology to model information of users using smart home applications. They divided the user ontology in two main components, one component related to static information of the user (such as name and age) and the role of the user (whether the user is a resident or a visitor) and another component related to the profile data of the user (such as heart rate recorded) and preferences (preferred activities).

In (Paganelli & Giuli, 2007), it is proposed an ontology-based context modelling approach for a home care assistance scenario where it is defined a Patient Personal Domain Ontology where it is identified different relevant context items related to patient physical data (such as biomedical acquired values), location and activity. These data is then used to automatically infer patient current health status and detect and alert problematic or dangerous situations and events.

Figure 4. Person profile ontology, adapted from (Zografistou, 2012)

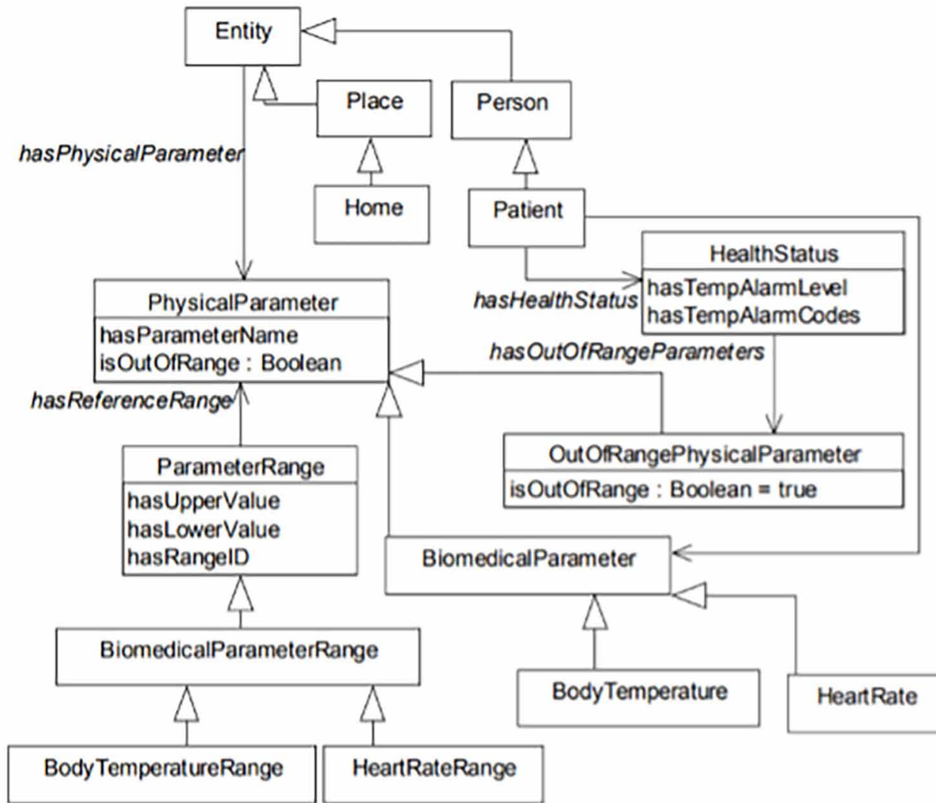



## b. Domain Ontologies

*Domain* specific ontologies allow the user to model domain specific concepts and relations. This type of ontology usually focusses on one specific modelling target or area of application, such as healthcare or assisted living. Domain ontologies allow the reuse of complex models that usually require extensive expertise input. Furthermore, domain ontologies can be easily combined since they use same semantic model. In (Paganelli & Giuli, 2007), authors also propose the use of Home Domain Ontology which contains relevant context data related to the monitoring of environmental parameters (such as temperature and relative humidity) and then also detect dangerous environmental situations (for example, detect a gas leak or even a fire inside the home environment).

In (Zografistou, 2012), it was also proposed a Health Domain Ontology which describes all the basic concepts required to model and support the daily treatment of a disease. The authors proposed a schema for which the knowledge base keeps the information provided to identify problematic situations and detect diseases which the inhabitants may suffer. This domain ontology considers four main classes which are: Disease (it is modelled each disease the inhabitant may have and the level of gravity), Symptom (symptoms that may occur to the patient and that are relevant to identify a disease), Treatment (describes

*Figure 5. Patient personal domain ontology, adapted from (Paganelli & Giuli, 2007)*




the type of treatment required to deal with the disease including medication, actions and measurements), and Restriction (restrictions associated to the disease which affects activities, environmental conditions, medication and nutrition).

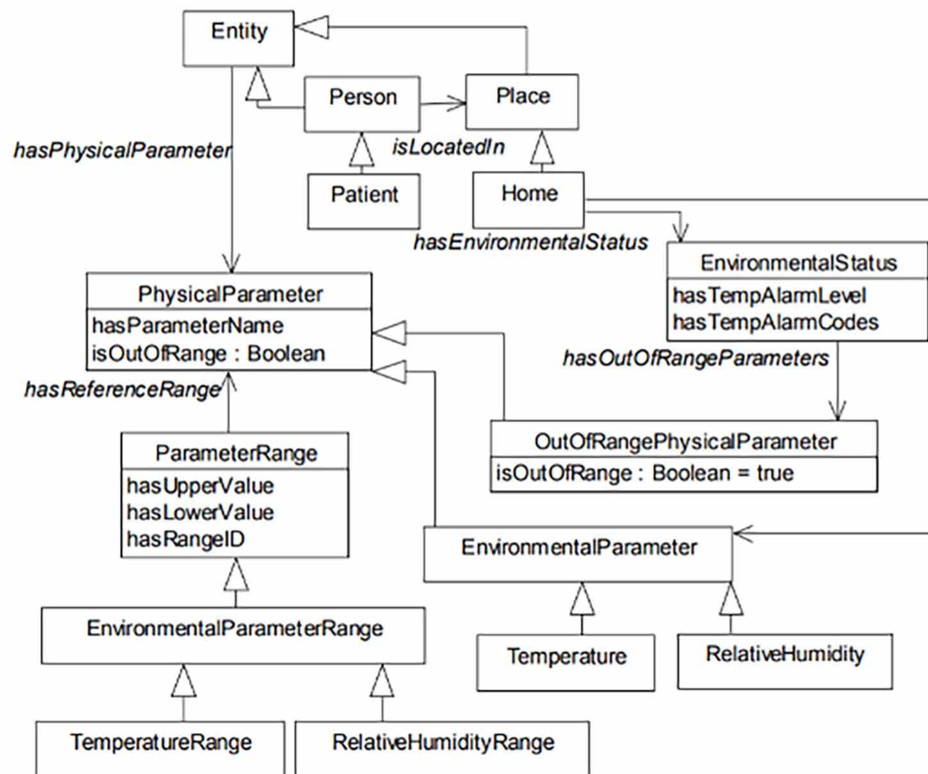
## Recommendation Systems

There are numerous options of methods to be employed in recommender systems, however, they still suffer from critical limitations and drawbacks. The methods implemented in recommender systems can be divided into two main classes: collaborative filtering and content-based methods (Lucas et al., 2013). In collaborative filtering methods the recommendation process is based on products' opinions collected from other users. Content-based methods compare text documents to user profiles, where web objects are recommended to a user based on those he has been interested in the past (Lucas et al., 2013).

"Deep learning is a subset of machine learning, which is essentially a neural network with three or more layers." (IBM Cloud Education, 2021) The typical defining essence of deep learning is that it learns deep representations, that is, it learns multiple levels of representations and abstractions from data (Zhang et al., 2019).

Recently, deep learning has been applied to recommendation architectures to bring more improvements in the performance of recommender systems based in more traditional approaches (Zhang et al.,

*Figure 6. Home domain ontology, adapted from (Paganelli & Giuli, 2007)*



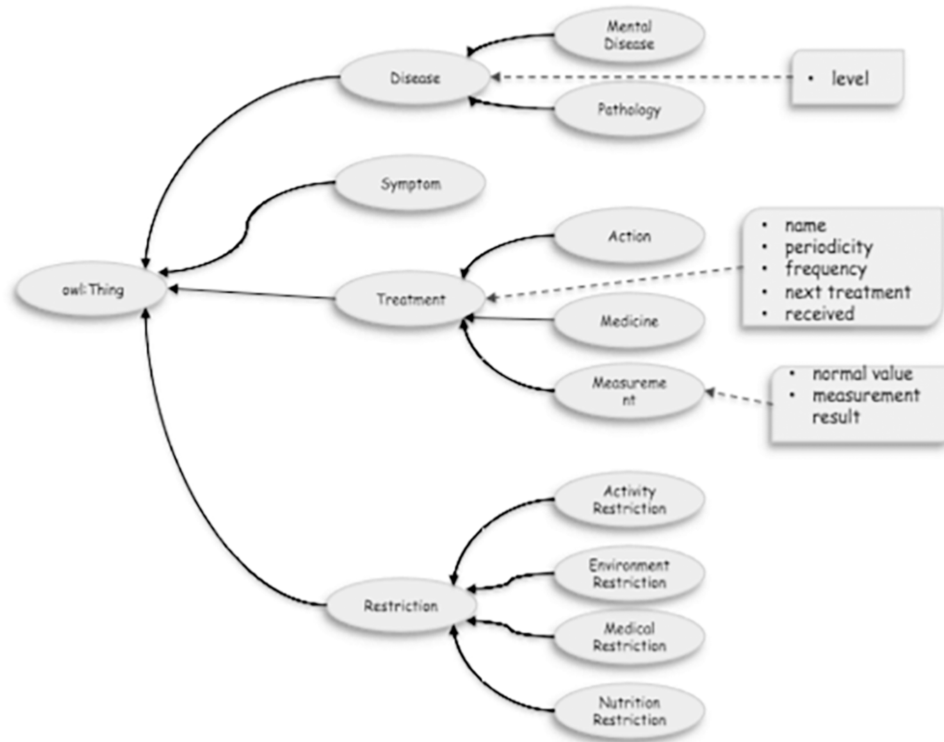

2019). Recent advances in deep learning-based recommender systems have gained significant attention by overcoming obstacles of conventional models and achieving high recommendation quality (Zhang et al., 2019). Deep learning can effectively capture the non-linear and non-trivial user-item relationships and enable the codification of more complex abstractions as data representations in the higher layers. Furthermore, it catches the intricate relationships within the data itself, from abundant accessible data sources such as contextual, textual and visual information (Zhang et al., 2019). Between the most frequent deep learning architectures applied to recommender systems we find Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and variants of RNN, like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU).

## Natural Language Processing and Machine Learning

Natural language processing (NLP) is generally used in healthcare systems that require data from multiple sources, not always digital. The use of NLP allows capturing information that is unclear or otherwise unstructured. From this transformation, information becomes more accessible and capable of being used in a more versatile way. An example of an application is automatic report writing, in which the doctor dictates the content of the document.

NLP allows computers to analyse, understand, and derive meaning from text and speech similarly to how humans do. NLP is part of the larger artificial intelligence (AI) landscape, drawing from fields

*Figure 7. Health domain ontology, adapted from (Zografistou, 2012)*




including computational linguistics and machine learning in its algorithms to convert unstructured data into actionable information. (Rebhan, 2019) The unstructured sequence of tokens (word or characters) is transformed in numeric data that is then filled in diverse types of algorithms able to perform a variety of distinct types of tasks. These tasks include text summarization, sentiment analysis, information retrieval from text or speech, part-of-speech tagging, text classification, language translation, named entity recognition, among other tasks.

The application of NLP has an enormous potential in psychiatry because language-based deficits are common symptoms of depression, behavioural disorder, ASD, personality disorder, and schizophrenia (Cohen et al., 2014).

NLP has various applications in health care. These techniques can be used to assist health care professionals in tasks such as assisting with clinical documentation, obtaining diagnosis of the mental health illness, and supporting clinical decision-making. Another area where NLP can used is supporting mental health treatment. Although the evolution of NLP techniques is recent and its adoption in the mental health field is just beginning, there are studies and applications that show its potential.

In the area of diagnosis, NLP can be used for early detection of cognitive decline and mental disorders, or to detect risk situations.

Emotions and mental health influence the method of communication and the choice of words. Mental health professionals can evaluate free speech to help identify and predict psychiatric illness in patients. The NLP techniques can be explored to develop automated speech analysis systems to predict mental problems.

Several studies have demonstrated the NLP techniques con be fruitful to detect specific emotions, to detect distress/suicide ideation, to measure stigma, to measure mood valence, or to detect depression (Calvo et al., 2017).

In one proof-of-concept study (Bedi et al., 2015), researchers tested how NLP and machine learning could help predict psychosis onset in a group of teenagers and young adults. Each of the study participants had a baseline interview and was assessed quarterly for up to two and a half years. Using transcripts of the baseline interviews, researchers fed speech features into an algorithm and found that features such as semantic coherence and speech complexity had a significant correlation with eventual psychosis development - predicting psychosis onset with 100% accuracy.

Seniors can also benefit from this type of NLP functionality. The increasing senior patient population puts additional stress on health care providers to incorporate recent technologies for early identification of various geriatric health risks. One area where NLP can assist is with identifying speech alterations that signify cognitive decline (Beltrami et al., 2018) (e.g., Alzheimer's disease), as impaired speech is often an early symptom of preclinical stages of dementia.

NLP and machine learning algorithms can also evaluate free text (e.g., electronic health record notes, patient portal messages) to help predict patients who may be at risk of self-harm or psychological distress, enabling care teams or other caretakers to intervene faster. For example, health providers can evaluate patients' mental health based on what they post on social media sites or to online blogs/message boards. Given the widespread adoption of social media and mobile devices, health care providers have a wealth of new data to work with. Feeding patient-generated text into NLP and machine learning algorithms, caregivers can create predictive models that signal when a patient is experiencing deep depression, undergoing an anxiety attack, or having suicidal thoughts (Coppersmith et al., 2018).

Within health care, providers can leverage NLP to predict people's mental states to proactively reach out to patients through phone or text, or they can create "online pathways" (Calvo et al., 2017) that direct patients to digital peer groups, counselling, psychotherapy, or mental health educational websites.

Mental health conditions can often be treated with counselling and psychotherapy, and in recent years there has been rapid growth in the availability of these treatments thanks to technology-mediated counselling. Technology can be used to improve the conduction of counselling sessions by analysing many conversations and finding the most efficient strategies. The Stanford Natural Language Processing Group conducted a study (Althoff et al., 2016) through a large-scale study of crisis counselling conversations. Applying techniques such as sequence-based conversation models, language model comparisons, message clustering, and psycholinguistics-inspired word frequency analyses, the authors were able to discover actionable conversation strategies that are associated with better conversation outcomes.

NLP based systems can help health providers go through data resources in text format to be able to offer more personalized and preventive care (Xtelligent Healthcare Media, 2021). Delivering care that is personalized to the user is major goal of AI-powered chatbots. Alison Darcy, a clinical psychologist at Stanford University, created Woebot based on cognitive-behavioural therapy, which encourages people to examine how they react to challenging situations (Fitzpatrick et al., 2017). This chatbot is based on cognitive behavioural therapy principles. It has an empathy component that is tailored to the messages that the individual sends and is designed to target cravings and urges and to help the individual build self-awareness in terms of their patterns of thinking, mood-related thinking, anxiety, depression, as well as the urge and craving to use. However, the bot is not a replacement for an in-person therapist. Instead, the tool is part of a widening array of approaches to mental health, and it is fundamentally different from any other form of therapy. These kinds of systems will not take place of a counsellor, neither will

directly interact with a person who might be in crisis. Instead, they are designed to work in partnership with counsellors. Another advantage of these kind of systems is its ability to detected risk situations and raise alerts sent to a mental health professional accompanying the patient.

Another advantage of AI-driven tools, such chatbots is the increased access (Xtelligent Healthcare Media, 2021). Chatbots can interact with an individual in real time. They are available 24/7, at no cost, and they reduce stigma in terms of accessing treatment. Whether these tools are used as stand-alone treatment agents or as an adjunct to more traditional counselling, chatbots provide added therapeutic content. (Xtelligent Healthcare Media, 2021).

## Case Studies

ICT and AI have gained a prominent role in the management and delivery of health care and social assistance. There is a growth in AI applied to health with high mobility, connectivity, and processing capacity. But some of the features developed do not allow its users to better manage their quality of life, for example, issuing alerts with recommendations adapted to the user's profile or providing problem-solving strategies to deal with lifestyle or disease risk factors or other specific everyday situations.

ICT and AI application in eHealth, namely in mental care seem to contribute to help their users to engage in health promoting behaviours outside the clinical context (Harrison et al., 2011)(Luxton et al., 2011) or in other activities such as therapeutic homework, facilitating generalization to the day-to-day life of its users (Ben-Zeev et al., 2015).

The use of mobile devices seems to be the logical path for self-management. More than self-management, mobile devices may help alerting patients, therapists, and caregivers in more faster way than traditional methods. They also allow to interact in different manners with patients and therapists.

Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD) has contributed to the implementation of innovative solutions in the field of AI and PA, Recommendation Systems, Medical Informatics and Mental Care on the scope of previous projects. Some of these projects that we consider relevant are presented below.

### SmartHealth

The scientific vision of this project focus on augmenting the knowledge, information, and interaction at the disposal of agents, robots, and humans to improve their performance in the healthcare ecosystem. Namely is to blend Artificial Intelligence (AI) with Personal Assistant (PA) to build a recommendation system that, using specific algorithms and knowledge database, may help people with mental disorders, namely anxiety disorders by reducing the response time to episodes or even prevent those same episodes from happening.

A number of practice guidelines fairly consistent have been published on the treatment of anxiety disorders in the last years (American Psychiatry Association, 2017)(Katzman et al., 2014)(Baldwin et al., 2014)(Bandelow et al., 2012)(Borwin et al., 2012). They confirm that anxiety disorders can be treated mostly on an outpatient basis and are responsive to intervention, and that effective treatments include pharmacological approaches, psychological approaches and combinations of these treatments.

Smarthealth project allows and helps therapists and patients to interact with the purpose of minimizing response times to people anxiety episodes, it also allows patients to self-management and gives feedback to the therapist.

The Smarthealth mobile app, integrate AI algorithms, used by the PA and a recommendation component.

The Mobile App and web platform enable the user to Manage anxiety episodes beyond the medical context. Receive recommendations in order to adjust lifestyle habits, reduce anxiety disorders risk factors, promote independent living, and so on, supporting the person in their efforts to change and define a set of goals or tasks to accomplish.

The functionality of Anxiety Problem Solving describes a cognitive-behavioural therapy (CBT) tool. This tool can be considered a way of interaction and a place where the user can describe and manage a stressful situation in a safe space while working to find a possible solution for the problem.

CBT is a talking therapy that attempts cognitive and behavioural change based on an individualized formulation of a user's personal history, problems, and goals. In general, the evidence-based of CBT is very strong when applied to anxiety disorders. CBT models emphasize the importance of cognitive appraisals (reasoning biases) and emotional dysfunction on the appearance and maintenance of symptoms. Thus, it is necessary to work on reducing distress and stressful environments and managing negative schemas and reasoning biases.

Chill Out Tools feature offers the user not only stress management skills but also a relaxing environment with access to media files to view or listen. Mindfulness, the process by which one attends to present-moment sensations, thoughts, emotions, and experiences in a non-judgmental manner, has been reported to exert beneficial effects on health and well-being, both in non-clinical and clinical samples. Mindfulness has consistently been associated with lower rates of anxiety.

The mobile app has been designed to generate a low cognitive load and it have a simple and intuitive interface: the use of pictures rather than text; reduced sentence lengths; inclusive, non-clinical language.

## FoodFriend

The quality and quantity of the food we eat affects our health and mental disorders. Population frequently suffers from diet-related diseases and their management and treatment brings additional concerns over the sustainability of healthcare systems. One evident factor that contributes to this issue is disease-related malnutrition. In fact, malnutrition has serious negative consequences for the health and mental illness of the patient and leads to a slower recovery, more serious complications, and increased mortality. As a result, we observe longer hospital admissions, weak response to medical treatment and increased use of medication, which demands for an increase in healthcare costs.

Malnutrition and poor diets can be observed in several different contexts. For example, in cases where the patient cannot eat any food because of a mental illness, has a decrease in appetite, difficulties in swallowing, or some type of surgery that interferes with eating.

Overall, it becomes clear that the patient him/herself should have an active role in the disease management process and this will contribute positively to improve a healthier ageing, allow the definition of more personalized and efficient ways to support the patient and as a result improve health and mental outcomes in an improved cost-effective manner (Wu et al., 2017).

In this context, the Food Friend project was established and is focus on the development of secure, innovative, and user-friendly technology for food intake related data acquisition, storage, analysis, and visualisation and for providing feedback and recommendations under the different malnutrition contexts that were presented.

### Personal Health Empowerment

One of the most impactful global challenges we are currently witnessing is an increase of the world's population which is growing older. With the prevalence of chronic and mental diseases within this age group we observe an increase in the healthcare costs. Patients require regular medical consultations and constant monitoring of their health and mental health throughout their daily lives. Healthcare, namely mental care has traditionally been provided through either face-to-face intervention between the patient and the healthcare professional, separated by periods without structured support or using self-monitoring tools (such as flow meters, handheld spirometers, oximeters) and self-management tools (such as symptom diaries, manuals, pamphlets, and web resources) between consultations. The reality, however, is that the constant monitoring of patients' condition has become a burden on the healthcare providers (Gibson, 2013) and traditional healthcare delivered through health professionals' face-to-face interactions becomes more difficult to achieve. As such, the necessity to develop cost-effective solutions to monitor and treat patients with has increased significantly in recent years (Gobbi, 2015).

Healthcare providers have noticed the importance of the person or patient him/herself in the management of his/her health and mental condition, and the importance to include him/her into the process in an active role. As a result, new healthcare paradigms have emerged with the development of preventive solutions to help the person adopt a healthier lifestyle by providing him/her with tools to actively participate in the treatment of his/her diseases, and this way, decreasing the burden on healthcare personnel and costs. In this scope, concepts such as mobile health (mHealth) has emerged towards the self-management of the patient's disease, by developing mobile systems that are capable of monitoring patients' health and mental status and giving customized feedback about activities and behaviours that can be done to improve health and mental wellbeing (Steinhubl et al., 2013)(Luxton et al., 2011).

Personal Health Empowerment (PHE) project here presented, was established with the main goal to empower people to monitor and improve their health using personal data and technology assisted coaching. To achieve this goal, PHE has applied innovative and intelligent measuring and monitoring tools for preventive healthcare and allow cost-saving and self and home-care solutions with increased patient involvement.

The project innovations revealed a significant impact on healthcare and mental sanity to the patient, providing both evidence and means to realise people-centric and preventive healthcare, and allowed for cost-saving self- and home-care solutions with increased patient involvement.

## CHALLENGES AND CONCLUSIONS IN THE APPLICATION OF AI TO MENTAL CARE

AI systems could help to offer more personalized and preventive mental care and approach mental illnesses in a more targeted way. The capacity of analyse of genetic data can unlock the key to understanding mental health. Neuroimaging can help to understand how the brain works.

The data quality can be particularly challenging when it comes to mental healthcare. The data used to train AI models is a crucial aspect of their clinical utility – and data quality can be particularly challenging when it comes to mental healthcare. The intelligent system will be only as good as the data it's trained on and the people that are using it. The data used to train these models must be diversified because if we only take one region, one clinic, or one population, these algorithms are going to have very limited

utility. These tools must be built from the ground up with a very diverse approach – we must work with the patients, as well as consider input from clinicians, data scientists, and regulators.

The role of data and information has always been crucial for decision making and the provision of Mental healthcare. With the increased digitization in healthcare, an immense amount of data is also generated from other segments of the healthcare industry than hospitals and healthcare providers, for example, medical insurance, medical equipment, life sciences and medical research. There are several different channels to collect this data. A new source is social networks. For instance, Twitter feeds can be used to try and predict the onset of depression. Currently, access to large volumes of data allows to support the development of a wide variety of medical and health care services. The emergence of advanced analytics, machine learning and AI techniques alongside, provides various possibilities for transforming this data into meaningful and actionable insights to support decision making, provide high-quality patient care, respond to real-time situations, and save more lives on the clinical front. With the use of analytical techniques, healthcare stakeholders can harness the power of data not only for analysis of historical data (descriptive analytics) but also for predicting future outcomes (predictive analytics) and for determining the best action for the current situation (prescriptive analytics). From the dissemination of communication and information technologies in mental health, AI and machine learning, in particular, appear on the basis of the development of applications for solving problems of prediction, monitoring and treatment for mental health care.

The role of AI in mental healthcare that has the most potential to make an impact now, is supporting human therapists and the use of Personal Assistant to help them. In the application area of PA, numerous researches and developed systems already seem to promise good results, but yet some experimentation and implementation are still necessary to conclude about the utility of the PA in Mental healthcare context.

The analysis, application, implementation, integration, and evaluation of Artificial Intelligence techniques to be used in the contextual PA will allow management and monitoring by health beyond the medical context, as well as the assertive adjustment of some lifestyle strategies, and reduce anxieties risk factors. It will contribute to improve lifestyle habits of the user by suggesting changes in user behaviours (individual and collective) and support the prevention of mental disorders.

Healthcare apps can be used to deliver medication alerts, patient education material and human-like interactions to gauge a patient's current mental state. The application of AI in the form of a contextual personal assistant can have an incredible impact on monitoring and assisting patients with some of their needs when clinical personnel are not available. Making the services available 24/7, in real time at no cost, and they can reduce stigma in terms of accessing treatment.

Intelligent Mental health apps can target a broad range of functions: self-management, cognition improvement, skills-training, social support, symptom tracking, and passive data collection. Also, intelligent mental health apps span all stages of clinical care provision, including immediate crisis intervention, prevention, diagnosis, primary treatment, a supplement to in-person therapy, and post-treatment condition management. Intelligent mobile apps are a good choice for psychological treatment delivery compared to other platforms due to ease of habit, low effort expectancy, and high motivation, especially in young people (Marshall et al., 2013).

Accompanying patients with mental diseases in the exam room is not enough. "Care providers who treat patients with chronic diseases recognize the importance of maintaining contact with their patients outside of the exam room." (Chouffani et al., 2018) With today's AI capabilities and mobile apps, patients can receive feedback on several data elements captured on their phone or wearable devices. Whether it relates to medication adherence or is simply a motivational voice that encourages fitness activities and

healthy habits, AI as a personal life coach creates a customised experience for each individual patient and offers proactive alerts that can be sent back to physicians.

Several practice guidelines have been published on the treatment of anxiety disorders. They confirm that anxiety disorders can be treated mostly on an outpatient basis and are responsive to intervention and that effective treatments include pharmacological approaches, psychological approaches (particularly cognitive and behavioural treatments), and combinations of these treatments. Indications for hospitalization include suicidality, unresponsiveness to standard treatments, or relevant comorbidities, such as major depression, personality disorders, or substance abuse.

A new approach to solve this issue will combine the best evidence in the integrated treatment of these specific mental health problems, with strategies for empowerment and promotion of self-care.

Also, AI technology holds great promise to transform mental healthcare and can identify mental health problems at an earlier stage when interventions may be more effective, and personalize treatments based on an individual's unique characteristics. Thus, there is a scope of opportunities to use intelligent mobile apps to deliver interventions as a supplement to in-person therapy or/ and as a mechanism to treat sub-clinical anxiety conditions that may lie below the threshold for anxiety disorder treatment.

Information technology and PA can promote illness self-management, which has been shown to be effective (Bricker, 2014), and applied for example to e.g., smoking cessation (Ly, 2014) and stress management (Keyworth, 2018).

In addition to the benefits provided, there are a number of significant barriers to using the technology in mental healthcare.

The big challenge for mobile health applications is making that the user come back and interact with it on a regular basis. In other words, with smartphone apps and chatbots, patient engagement is a key factor in determining the success of the technology. With smartphone apps and chatbots, patient engagement is a key factor in determining the success of the mental care treatment. Typically, the more the individual uses the mental health application, the greater the benefit he'll get from it. Anything that can be done to boost engagement should help with outcomes in terms of accuracy and effectiveness.

To prevent risk situations, it is important that these tools were equipped with appropriate protections for high-risk patients. These systems must have safety features built into it, like language detection and rules for risk management. In case of a risk situation is detected, the system must generate an alert directed to the health professional (Xtelligent Healthcare Media, 2021).

NLP can for example enhance speech analysis to predict psychotic disorders in young people from high-risk populations. NLP can allow the study of the individual's psychological degeneration and the presence of symptoms in the patient's speech. Lack of thought organization is a typical symptom of schizophrenia and is usually diagnosed based on behavioural analysis and clinical observation. The NLP used as a basis for the semantic and coherence analysis in an interview using, for example, specific scripts to verify several parameters, can allow the application of a syntactic analysis model to analyse the coherence and phrasal construction of the discourse.

The definition of models that allow analysing the coherence and phrasing of speech, that is, if semantically similar words co-occur in texts with consistent topics more often than unrelated words, then the semantic similarity of two words can be quantitatively indexed to frequency of its co-occurrence in a sufficiently large set of texts. The use of these techniques can show a relationship between the structure of the discourse and the probability of developing a schizophrenic condition.

Robots that are marketed for example by Paro (http://www.parorobots.com/) try to simulate a pet so that elderly patients maintain some cognitive and social skills. Robots are equipped with various sensors

of different nature to be able to produce feedback on the patient's behaviour. Using machine learning techniques with enhanced learning, robots can recognize positive behaviours such as petting. On the other hand, they are also able to change their personality to avoid negative actions suffered by the patient.

So far and to our knowledge there are no official standards to guide the use of AI and other emerging technologies in mental healthcare. Clearly, there is a need to integrate ethics into the development of AI. In this context, Privacy and Data security issues are a key role in the success of any AI project in Mental Care. It will be necessary to establish and develop ethical and privacy management plan for the user and application requirements analysis and the user studies involvement. The plan can ensure the safeguard of ethical and privacy rights of all involved end-users. The new European Union Regulation RGPD 2016/679 must be respected in relation to the user's saved data.

In Mental Care, there will always be a need for human-to-human connection and interaction. AI's role in this space shouldn't be to replace humans, it should be to support them.

Mental health is a huge challenge in our society, and the COVID 19 pandemic is only increasing the scope of that challenge. AI has the potential to alter dramatically mental healthcare, ultimately making mental care more accessible, responsive and reasonably priced.

The use of mobile devices seems to be the logical path for self-management. More than self-management, intelligent mobile devices may help alerting patients, therapists and caregivers in more faster way than traditional methods. They also allow to interact in different manners with patients and therapists.

The goal is to blend AI with PA in order to build recommendation that, using specific AI algorithms and knowledge database, may help people with mental disorders by reducing the response time to episodes or even prevent those same episodes from happening. The challenge will be to allows and helps therapists and patients to interact with the purpose of minimizing response times to people with mental disorders and Improve Independent Living.

However, it will be necessary to validate and see the impact of using artificial intelligence on mental health recommendation systems.

## ACKNOWLEDGMENT

This research work was supported by National Funds through FCT under the project UIDB/00760/2020.

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