5G4P Health

D2.1 SotA

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Executive Summary

The 5G4PHealth project leverages emerging 5G, AI, and IoT technologies to advance healthcare services, focusing on Predictive, Preventive, Personalized, and Participatory (P4)-based solutions. This SOTA report provides a comprehensive review of existing approaches, methodologies, and technologies relevant to the project's objectives in digital healthcare. The report covers advances in AI diagnostics, wearable technologies, and patient data management systems, while also highlighting the gaps and challenges that the 5G4PHealth project aims to address. This report summarizes the current state-of-the-art in healthcare technologies, focusing on AI-driven diagnostics, 5G-enabled communication protocols, and IoT-based patient monitoring. It identifies existing gaps in P4 healthcare services and explores potential avenues for innovation in terms of data management, patient-centric services, and secure health information systems. The SOTA is aligned with the key objectives of the 5G4PHealth project, including the development of AI-powered solutions for healthcare, integration of IoMT for real-time monitoring, and implementation of 5G technologies for low-latency communication. This document supports the design and implementation of innovative healthcare tools by providing a detailed review of the latest developments and best practices.

The report is structured as follows:

- Section 1 reviews existing approaches in AI and IoT applications for healthcare and discusses 5G technologies and their implications for health data transmission.
- Section 2 analyzes patient data management and security frameworks.
- Section 3 provides a critical evaluation of current regulatory frameworks and standards.
- Section 4 identifies gaps and proposes future research directions.

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1 Current Approaches and Technologies in Healthcare

5G4PHealth project aims to innovate the patient experience, diagnosis and treatment in specific healthcare environments through the application of 5G technology, innovative AI-driven services and enhancement of personal health records. It proposes a smart healthcare digitalization approach that integrates various technologies such as electronic health records (EHRs), communication technologies (e.g., 5G), artificial intelligence (AI), Internet of Medical Things (IoT), and smart analytics into the healthcare system.

1.1 AI-driven Healthcare

Artificial intelligence (AI) refers to computational technologies that mimic various aspects of human intelligence, including cognitive processes, deep learning, adaptability, interaction, and sensory comprehension[1] [2]. These technologies have an interdisciplinary approach and can be applied to different areas within medicine and healthcare[3] and to different processes, such as diagnosis, treatment, and patient experience. In fact, major hospitals are, at present, using AI-enabled systems to augment medical staff in patient diagnosis and treatment activities for a

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wide range of diseases[4]. The 5G4PHealth project focuses the application of AI to three important healthcare areas: Posture Evaluation for physiotherapy, Glaucoma Diagnosis, Depression Relapse Prediction and Patient Experience.

1.1.1 Posture Evaluation

Human movement information provides valuable insights into both body and brain activity. Additionally, analysis of human locomotion can be performed for various reasons, such as non-verbal communication, preventing collisions, optimizing athletic performance, and aiding rehabilitation. Since humans naturally learn and develop their locomotion from childhood, replicating this phenomenon in machines and computers is challenging. The first step requires accurately capturing human motion, and then using these data for machines' decision-making[5]. The very first interest in studying human motion dates back to the 1400s when Leonardo da Vinci tried to describe the mechanics of the human lower extremity during daily activities[6]. In the 1500s, Galileo Galilei attempted to investigate human biomechanical functions by using mathematical models[7]. Giovanni Alfonso Borelli, who is also known as the father of biomechanics, was able to derive the forces required for equilibrium in various human joints in the 1600's[8]. Borelli's successors, such as Isaac Newton, the Bernoulli Family, Leonhard Euler, Jean Léonard Marie Poiseuille, and Thomas Young, contributed to the development of biomechanics, either directly or indirectly, by advancing the principles of mechanics and fluid dynamics by the end of the 1800s[9]. In the late 19th century, Eadweard Muybridge was the first to employ motion picture capture to study motion[10]. One of the earliest examples of his attempt is "The Horse in Motion" which captured the movement of a horse in full gallop using a series of cameras set up along a track. Since then, several researchers have developed and employed different techniques to capture movement.
There are different kinds of instruments to record and analyse human locomotion such as goniometers, magnetic systems, Inertia Measure Units (IMUs), and optical systems[11,12,13]. Among them, optical systems are more commonly used compared to other methods due to their accuracy, reliability, and validity[14, 15]. Optical marker tracker systems are a very recent clinical gold standard for obtaining the position of human joints by using several markers on the human body and multiple stationary cameras. However, theoretically, each marker needs to be seen by at least two cameras. As a result, several stationary cameras need to be used during the trials, making the applications of these systems expensive, mobility-limited, and requiring a complex setup. As a solution, researchers have made some attempts to employ single-view image or video data combined with external computational methods to make the process low-cost, mobile, and user-friendly.

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Optical marker tracker systems have different classifications, including marker-based vs markerless-based, single-view vs multiple-view, two-dimensional (2D) vs three-dimensional (3D), Red-Green-Blue (RGB) vs Red-Green-Blue and Depth (RGB-D), and temporal filtering methodologies[11]. Each of the methods needs a set of specific equipment and instrumentation. Lawrence Gilman Roberts was the first person who put the first brick of today's Human Pose Estimation (HPE) in computer vision science in 1963. He investigated the extraction of the 3D information from a 2D image[16] [13]. Human Pose Estimation (HPE) is a term that refers to the ability of a machine to find the Cartesian coordinates, (x,y,z), of the joints of a human body in a 2D image or 3D space[17]. After L.G. Roberts's studies, several researchers started in-depth investigations on the HPE field using computer algorithms[18,19,20]. However, few researchers have implemented HPE techniques on the data extracted from only one stationary single camera to study human locomotion[21].

Among several human activities, lower-limb-related locomotion, including walking, running, and jumping, is one of the most common activities with several useful information on the health-wise status[22]. HPE techniques have been used to analyze the kinematics of the human lower limb, which involves measuring a range of spatio-temporal and kinematic variables, such as lower extremity joint angles. These variables enable researchers to have an insight into an individual's overall health. However, few researchers have investigated the application of single-camera markerless motion capture systems or HPE methods in the healthcare application[23,24,25].

Combined with novel deep learning models, video-based markerless approaches have shown competitive performance against marker-based methods in recent years[26,27]. Deep learning-based methods divide the gait assessment into several subtasks and train the specialized neural networks for each. Benefiting from abundant neural network architectures for various tasks, extensive datasets for human pose estimation, and remarkable generalization capability, deep learning-based methods have significant advantages in fast deployment for gait assessment.

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1.1.2 Depression Relapse Prediction

Depression is a significant contributor to the global burden of disease, characterized by its severity, high prevalence, and chronic nature[28]. While there are effective treatments available, their impact can vary among individuals, and there is often a delay in their effectiveness. Clinical decisions regarding depression treatment are frequently based on limited subjective information, resulting in suboptimal adherence to treatment guidelines. Additionally, healthcare systems often face resource constraints, leading to long waiting times for patients seeking psychiatric or psychotherapeutic care. In light of these challenges, it becomes crucial to enhance self-management strategies and improve communication between patients and healthcare providers to alleviate the burden of illness and address therapeutic gaps. Efforts to optimize depression management should prioritize interventions that empower patients, promote evidence-based treatments, and facilitate timely access to appropriate care to enhance treatment outcomes and overall well-being.

Clinical depression in adolescents

Clinical depression is one of the disorders that poses the greatest risk to contemporary public health. It is a phenomenon characterized by long periods of sadness, discouragement and irritability that alter the behavior and conduct of individuals and can lead to disabling effects or even suicide. It is a disorder that can occur at any age and is determined by various social and economic factors, among other physical and contextual reasons[29].

In recent years, global public health has focused on the prevention and monitoring of depression in various populations. Above all, the mental health of children and adolescents and the mitigation of the latter's risks of suffering from a depressive disorder have been a priority of health policies in most OECD member countries. In Europe alone, it is known that at least two million European minors and young people suffer from some type of mental disorder. Depression, which is in turn a leading cause of these conditions, affects 4% of adolescents between 12 and 17 years of age and 9% of 18-year-olds, a problem to which is added to the increase in anxiety and behavioral disorders[30].

Sánchez and Cohen[31] highlight the functional effects that depression entails in childhood and adolescence, recalling that suffering a depressive episode in these stages has a negative effect on school performance, growth and social relationships. If it is estimated that at least 20% of 18-year-olds will have suffered at least one clinically relevant depressive episode in their lives, the impact of this affectation on this population can be understood.

The authors also highlight the complexity of the diagnosis of depression in childhood and adolescence, due to the difference in its symptoms with respect to those manifested in adult life. They also associate depression in adolescents with substance abuse, eating disorders or the risk of developing bipolar disorder. These elements make depression one of the main risk factors for suicide in adolescents; in Spain alone, it is the second leading cause of death in young people between 15 and 19 years of age.

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This opinion contrasts with studies such as the one carried out in 2019 by Bernaras et. al. in which they concluded that both the treatment and prevention of depression in adolescents should be multifactorial in nature[32]. This is because in mental classifications childhood depression does not differ from adult depression, which forces specialists to take into account multiple explanatory theories to arrive at a complete understanding of depression.

This same study concludes that there are both biological factors and factors linked to negative interpersonal relationships and relationships with the environment, together with sociocultural changes, that influence the appearance of depressive disorders and may explain the observed increase in the prevalence of depression today.

Similarly, they stress that it is necessary to continue researching and delving into biological, psychological and social factors in an interrelated way, since the initial manifestations of depression can occur at a very early age and a complete study can explain the onset, development and treatment of depression. They also highlight that, although there are many instruments to assess depression and most treatments are becoming more rigorous and effective, it is still necessary to develop and implement prevention programs and continue to adapt diagnostic tests at an early age.

This urgency to know, diagnose and treat this pathology early in children and adolescents is clear among the scientific community. While research at the beginning of 2010 called for attention to be paid to depressive disorders, recent publications already speak of advances in this area and new needs as a result of research. Similarly, in recent years an effort has been made to diagnose psychopathological conditions and states of distress that were not previously considered relevant[33]. This has influenced the type of analyses carried out and the phenomena in which specialists have focused their attention, as well as the populations analyzed.

This has also prompted specialists to focus on biological and contextual factors that are not being attended to and also related to depression. Such is the case of executive functions, which have been the subject of increasing interest in research on depression in recent years, given the close relationship between depression and alterations in these functions.

Executive functions include skills such as inhibition, flexibility, and working memory. It has been observed that a good functioning of these functions plays a fundamental role in the prevention of mood disorders. Alterations in these functions have been identified in people experiencing depressive symptoms, suggesting that executive functions could serve as a tool to identify those at risk of developing depression early.

In the population suffering from depression, the assessment of the state of executive functions can be an indicator of the impact of the disease. It has been observed that the more these functions are affected, the greater the impact of depression on the person's life. In addition, a significant relationship between executive functions and suicide risk has been documented in individuals with depression.

An investigation carried out in Norway showed that there are associations between fatigue or loss of energy, loss of interest or pleasure, changes in appetite and sleep problems and

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[33] Martínez-Hernáez A. y Muñoz García A. "Un infinito que no acaba". Modelos explicativos sobre la depresión y el malestar emocional entre los adolescentes barceloneses (España). Primera parte. Salud mental. Vol. 33, No. 2, 2010. 145-152

concentration difficulties with poor executive functioning[34]. Based on an executive functioning model carried out for this research, it was based on the measurement of inhibition, displacement and updating capacities. The main argument of the study is that reduced executive functioning and depression symptoms are mainly linked through fatigue.

Using this bifactorial model with the aforementioned research, other recent studies have shown that depressive symptoms are primarily associated with common executive functioning in both adults and youth[35]. Because of this, the cognitive assessment of executive functions in people with depression could play a crucial role in the early identification of depressive patients at risk of suicide, which would allow the implementation of effective preventive measures. This approach is especially relevant in adolescence, as this phase of life entails unique vulnerability factors. Executive functions play a critical role at this stage, and any alteration in them can have a significant impact on the present and future of young people.

In addition, the topic of the relationship between adolescence, depression and suicide has gained great interest in both the media and the scientific community in recent years. The influential role of executive functions in this scenario has been recognized, as well as the possibility of modifying them through intervention strategies. This opens up new perspectives for addressing the prevention and treatment of depression in adolescence, taking into account the crucial importance of executive functions in this process.

Artificial intelligence is the protagonist of this process, even though there are still challenges to be solved in terms of accurate diagnoses and interpretation of data, among others.

Relationship Between Executive Functions and Depression in Adolescents

The relationship between executive functions and depression in adolescents is based on a solid theoretical and empirical basis. Executive functions comprise a set of high-level cognitive skills that control and regulate mental processes such as planning, decision-making, working memory, and self-control. These skills are essential for adaptive functioning in daily life.

Numerous studies have shown that adolescents who experience depressive symptoms often exhibit deficits in executive functions. For example:

- Decision-making difficulties: Teens with depression tend to make impulsive decisions or avoid making important decisions due to a lack of motivation and decreased interest in the future.
- Problems with planning and organization: Depression can affect teens' ability to plan tasks, set goals, and carry out daily activities.
- Self-control and emotional regulation: Depressive symptoms are often associated with difficulties in emotional self-control, which can lead to impulsive behaviors and mood swings.
- Working memory and attention: Depression can affect working memory and attention, resulting in difficulty concentrating on academic and everyday tasks.

The scientific literature supports the idea that deficits in executive functions can be both a cause and a consequence of depression in adolescents. This two-way relationship

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underscores the importance of assessing and monitoring these cognitive abilities in at-risk adolescents. Thus, executive dysfunction can be both a cause and a symptom of depression. It can manifest as a symptom due to the association between depression and reduced metabolic and neural activity in brain regions crucial for executive functions[36]. In major depression, executive deficits commonly involve problems related to planning, initiating, and completing goal-directed activities.

On the other hand, executive dysfunction can also contribute to the development of depression, with fatigue being the factor mediating the relationship between them[37]. Executive dysfunction can make it difficult for people to perform daily tasks, leading to feelings of frustration, reduced self-esteem, and ultimately depression. Therefore, executive dysfunction and depression are intricately linked, and addressing both issues is critical to improving overall mental health.

Inhibitory control refers to the ability to maintain goal-directed behavior by suppressing overbearing responses or ignoring irrelevant stimuli[38]. The relationship between inhibitory control and depression is complex and not yet fully understood. Some studies suggest that better inhibitory control is associated with fewer depressive symptoms, while others suggest that depression is associated with deficits in inhibitory control[39].

Working memory refers to the ability to retain and manipulate information in the mind for a short period of time[40]. There is evidence to suggest that depression is associated with deficits in working memory[41]. Depressed people may show lower accuracy and longer response times compared to controls during working memory tasks[42] .

Cognitive impairments, including deficits in working memory, are common in depression and may be related to changes in brain structure and function. Some studies have found that impaired working memory in depressed patients affects all elements of working memory, such as attention allocation, phonological looping, and visuospatial sketchpad[43]. Other studies have found that depressed people show deficits in updating the working memory of both negative and positive content. In summary, the relationship between working memory, inhibitory control, and depression is strongly supported by scientific evidence.

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1.1.3 Patient Experience

The field of AI for patient experience in healthcare is rapidly evolving, with ongoing advancements and innovative applications, such as **1) Natural Language Processing (NLP):** NLP techniques are being used to develop chatbots and virtual assistants capable of understanding and responding to patient queries and concerns. These AI-powered systems can provide personalized health information, appointment scheduling, medication reminders, and general support, enhancing the overall patient experience and accessibility of healthcare services. NLP-based chatbots are being used for patient guidance[44], chronic patient support[45], monitoring optimization[46] or promoting healthier lifestyles[47]. **2) Sentiment Analysis:** AI algorithms can analyze patient feedback, reviews, and social media posts to understand patient sentiment and satisfaction levels[48]. Sentiment analysis enables healthcare providers to identify areas of improvement, address patient concerns promptly, and personalize patient care based on their emotional needs and preferences. Techniques such as Facial Expression Recognition (FER) through deep learning have known advancements which increase their effectiveness, achieving a high accuracy is still a challenging task[49] and challenges remain with partial face occlusion or lack of proper training datasets. However, the lack of the single-modal emotional information and vulnerability to various external factors lead to lower accuracy of emotion recognition. Therefore, multimodal information fusion for data-driven emotion recognition has been attracting the attention of researchers in the affective computing field[50]. **3) Voice Recognition and Voice Assistants:** AI-driven voice recognition technology enables hands-free interaction with healthcare systems, allowing patients to control devices, access health information, and manage appointments using voice commands. Voice assistants, such as Amazon Alexa or Google Assistant, are being integrated into healthcare applications to provide personalized health recommendations, medication reminders, and educational content. **4) Virtual Reality (VR) and Augmented Reality (AR):** VR and AR technologies are being used to improve patient experience during medical procedures, surgeries, and rehabilitation. AI algorithms can enhance these immersive technologies by providing real-time guidance, personalized simulations, and monitoring patient progress, leading to reduced anxiety, better patient engagement, and improved outcomes. It is important to note that while these AI applications hold promise for enhancing patient experience in healthcare, ethical considerations, data privacy, and transparency must be prioritized to ensure patient trust and the responsible use of AI technologies.

Artificial Intelligence applied to the detection of depression and executive functions.

The global exponential increase in cases of depression has led professionals from various disciplines to contribute their knowledge to the mitigation of this problem. Advances in Artificial Intelligence have also made it possible to develop models and strategies aimed at collecting data and issuing alerts that contribute both to the prevention of depression and to the treatment of patients already diagnosed.

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[49] L. Zhang, B. Verma, D. Tjondronegoro, and V. Chandran, ‘‘Facial expression analysis under partial occlusion: A survey,’’ ACM Comput. Surv.,vol. 51, Apr. 2018.
[50] Jiang, Yingying, et al. "A snapshot research and implementation of multimodal information fusion for data-driven emotion recognition." Inf. Fusion 53 (2020).

Among the studies highlighted in the literature on data-based tools that incorporate Artificial Intelligence, analyses carried out among the adolescent population and that collect data from body records or words used by the subjects analyzed stand out. According to what was studied, they use different markers and base classifiers to stratify the data collected.

A 2018 study used an AI logistic regression model to detect depression (ELRDD) using speech characteristics among Chinese students entering higher education[51]. The authors trained the system to recognize facial expressions of happiness, contempt and disgust from recordings of students during a questionnaire that detected stress and another that detected depression. These expressions were then converted into normalized images for effective detection and an algorithm of vector support machines was used to classify emotions. The analysis yielded encouraging results, with a high level of accuracy of 75% for women and 81.82% for men, as well as an advantageous sensitivity/specificity ratio of 79.25%/70.59% for women and 78.13%/85.29% for men.

With a similar population, a study conducted at India's Amrita University in 2018 investigated depression-related facial expressions, as well as ideal methods of extracting them[52]. To do this, the researchers created a dataset of happy faces from the JAFFE database and then applied a Viola Jones' face detection algorithm for the detection of each face. Facial features of each face were determined using a Gabor filter bank of 40 filters, concatenating the vector of characteristics of each image to form a set of characteristics for training. In this analysis, the absence of happy traits indicates the amount of negativity in the video. By classifying the data into three levels (high, moderate and mild) the system provides information that recommends the necessary advice.

Other studies have used other sources of information such as the words used by the subjects analyzed. A study carried out in France for the CLEF eRisk 2018 developed a pilot with the objectives of achieving the early detection of signs of depression and the early detection of signs of anorexia from texts written by young users of the Reddit platform[53]. This pilot used two types of text representations, one with linguistic features and the other with text vectorization. To achieve a robust dataset, the researchers classified users as depressive and non-depressive. The user classified as depressive mentioned in their posts or comments that they had been diagnosed with depression. Meanwhile, the user classified as non-depressive did not mention any words related to depression. Both representations were combined in machine learning models showing successful results in the detection of depressive signs.

Like these, several studies have focused on the analysis of facial or linguistic features from AI to determine moods and other indicators that alert about depression and other conditions such as bipolar disorder. However, these types of factors lack precision due to, among other things, the complexity of human emotions associated with depression, which is not yet tracked by existing technology. Thus, even when the designed models are able to recognize a complex bank of facial or linguistic features linked to human emotions, they still have a considerable level of error due to contingencies such as the patient experiencing momentary feelings of sadness, disgust or contempt, rather than the prolonged emotional states expected in patients with depression[54]. The need for constant monitoring limits the capacity of action of these

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models, which can undoubtedly be taken advantage of when incorporated into more complex systems.

Other studies have focused on more complex determinants to recognize the symptoms of depression and prevent or warn about it. For example, research aimed at detecting depression through magnetic resonance imaging was based on the diagnosis of endogenous depression, a type of depression in which the primary cause lies in biological or somatic factors, as opposed to situational factors that occur in people's environments[55]. This study set out to discover what occurs in the brain and how neurotransmitters are influenced in a person with depression, proposing a method of predicting depression through magnetic resonance imaging. The images resulting from these MRIs were segmented and analyzed in two stages: first, the extraction of cerebral and non-cerebral tissue, and second, the isolation of areas of interest in the brain that can be used in the extraction of features. To make the classification, the authors of the study used different machine learning algorithms.

Several studies have used MVS and the K-classifier for treatment remission in patients with major depression. A general probability-based classification method was also proposed to predict depression. Similarly, attention has been drawn to the lack of experiments with Convulsive Neural Networks (CNNs) facial expressions and depression that are also efficient. However, despite developments in recent years, few studies have focused on sources such as executive functions as ideal markers for identifying depression. Among them is research carried out in Korean schools, where high educational expectations among children and adolescents are related to psychological risks, such as stress, depression, anxiety and even suicide[56].

This study demonstrated that the use of latent class growth analysis and Bayesian network learning are useful when classifying longitudinal patterns of Executive Function Difficulties (EFD) in elementary school students. This finding is an important precedent, as it can support children's development and prevent risks by pre-classifying children who may experience persistent EFD and tracing the causes.

On the other hand, there are recent Artificial Intelligence models, in particular specialized Deep Learning structures, capable of using text as input data for automatic analysis and classification. Their use in the automatic detection of depression from texts written on social networks has been studied[57]. However, although there are versions of this type of architecture capable of using audio instead of text as input data[58], their application to the automatic detection of cases of depression from voice recordings has not been explored in depth.

Depression continues to be a field to be explored from the dimension of executive functions from the use of machine learning tools, which is a necessity in the state of the art and an opportunity to explore the factors that enhance this ailment.

Recognition of vocal parameters in depression detection

Finally, and for the purposes of what is sought to be achieved in this project, it is worth mentioning that other parameters have been assessed for the recognition of different

55 K. Kipli, A. Z. Kouzani, and L. J. Williams, “Towards automated de- tection of depression from brain structural magnetic resonance images,” Neuroradiology, vol. 55, no. 5, pp. 567–584, 2013.
56 Goh, E.-K.; Jeon, H.-J. Application of a Bayesian Network Learning Model to Predict Longitudinal Trajectories of Executive Function Difficulties in Elementary School Students. J. Intell. 2022, 10, 74. https://doi.org/10.3390/jintelligence10040074
57 Sivamanikandan S, Santhosh V, Sanjaykumar N, Durairaj T. scubeMSEC@ LT-EDI-ACL2022: detection of depression using transformer models. InProceedings of the second workshop on language technology for equality, diversity and inclusion 2022 May (pp. 212-217).
58 Liu X, Lu H, Yuan J, Li X. CAT: Causal Audio Transformer for Audio Classification. InICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) 2023 Jun 4 (pp. 1- 5). IEEE.

conditions, motivated, among other things, by the rise of recent technologies such as Chat-GPT, which use Deep Learning models directly on the input.

In Spain, natural language processing has experienced a significant boom in recent years, driven by the participation of numerous companies offering consulting services and solutions in this field. This boom is due in part to the increasing integration of natural language processing into a variety of services, from customer support to search engines and applications of all kinds.

In this context, the focus of companies working on natural language processing is not limited to simply offering devices, but involves consulting, software implementation and maintenance services. This comprehensive support approach is essential to ensure that natural language processing-based solutions work effectively and are tailored to each customer's specific needs. For example, at a recent meeting of the Spanish government within the framework of the PERTE health project, around 100 companies attended. This suggests that the number of companies involved in this field could be even higher, possibly multiplying several times.

In the field of natural language processing with a focus on voice, several entities are exploring this area. Some of them focus on speech-to-text and semantic and linguistic content analysis, while others venture into detecting health problems through voice, including elements such as tone, pauses, and prosody. This approach is often referred to as "voice biomarkers."

Companies working in this field include Kintsugi, Winterlight Labs, Ellipsis Health, and Sonde Health. Sonde Health, for example, seeks to predict and issue health-related alerts through voice analysis. In addition, they have developed the Sonde Mental Fitness app, aimed at users experiencing stress and possibly depression. Although some of these entities have obtained certain validations of studies in hospitals, they are still in the process of obtaining approval from regulators such as the FDA in the United States or the EMA in Europe.

While natural language processing has represented great advances in healthcare, it still has great limitations on the accuracy of its data. For this reason, it has been surpassed today by the recognition of other patterns such as vocal parameters, on which the literature on depression is still scarce, but which have already been identified in the analysis of other conditions. These parameters are closely related to mental health and could play a decisive role in the identification and evaluation of these problems. These include a variety of factors such as vocal formants, fundamental frequency, tone of voice, and vocal tremor, among others whose study would represent an important contribution to the state of the art.

In this same context, it is relevant to mention that in recent years, there has been significant progress in the field of audio and text analysis from an artificial intelligence perspective. This breakthrough has led to an in-depth overhaul of traditional methods used in the analysis of mental health-related issues, such as depression screening.

In the past, addressing these issues involved a two-stage process. First, expert knowledge was applied and ad-hoc statistical methods were used to pre-process the input data, which could be audio or text. These steps sought to extract characteristics considered relevant for the analysis, such as semantic aspects or signals of intonation and emotion, as mentioned above. Once these characteristics were obtained, mathematical models, such as machine learning algorithms, were applied to estimate and predict the desired goal, in this case, the probability of suffering from depression.

However, today, this approach has become obsolete thanks to notable technological advances. The most recent technologies, such as Deep Learning models, allow a direct approach to the input data, be it text or audio, practically without prior processing, except for some standard normalizations. The need to apply expert knowledge and ad-hoc statistical methods to extract characteristics considered relevant has been eliminated. Instead, models are allowed to directly analyze the text or audio in its crudest form and extract the features relevant to the problem at hand. This change has been fundamental in the rise of these technologies and has revolutionized the field.

In text analysis, the state of the art is represented by Transformer models, which can analyze text directly and have been shown to be effective in predicting mental health problems, such as depression. This generic approach can also be applied to audio analysis, with some adaptations, allowing you to capture features, such as intonation, that would be lost in conversion to text. Although research in this area, where audio is used as input, is not as advanced as in text analysis, there are numerous studies that explore this possibility.

Thus, the construction of a system that incorporates artificial intelligence technologies to the analysis of audio, and specifically of vocal parameters, continues to be a relevant need in the state of the art. The application of these technologies would make it possible to capture certain semantic patterns directly on the text, while obtaining information at other levels that could not be captured in text, a development that would bring great advantages to the detection and monitoring of clinical depression.

1.2 5G Applications on HealthCare

5G network has great potential in revolutionizing various healthcare applications, e.g., remote patient monitoring, rehabilitative therapy, and augmented reality (AR) / virtual reality (VR) assistance for collaboration in surgery, by enabling faster and more reliable communications, facilitating remote healthcare services, and enhancing data collection and analysis functions. In detail, 5G advancements have the potential to enhance healthcare accessibility, quality, and patient outcomes, namely on: **1) Remote Healthcare monitoring:** 5G enables high-bandwidth, low-latency and high-reliability communication links to help deliver real-time remote monitoring services. It allows healthcare professionals and doctors to remotely monitor patients, conduct virtual consultations, and perform surgeries through robotic/operating systems, which can help provide patients with access to quality healthcare services regardless of geographical barriers. **2) Internet of Medical Things (IoMT):** 5G can support the application of IoMT devices, such as wearables, sensors, and medical devices. These devices can collect and transmit data in real-time, enabling continuous remote patient monitoring, early detection of health issues, and personalized treatment plans. **3) Medical Imaging and Diagnostics:** 5G can enable high-resolution medical imaging/video transmission, e.g., MRIs and CT scans, which can help doctors quickly analyze the data, conduct remote consultation and make better and fast decisions based on image and videos transmitted via 5G networks. As the deployment of 5G networks and beyond continue to expand and evolve, it is expected to see more innovative medical applications that can improve patient care, remote monitoring, decision-making and enhance operational efficiency, which drive this research.

Fig. 1. Typical Communication Systems

Wireless technologies have evolved significantly during the past few decades, with nearly every ten years having a new generation of communication technology from 1G to now 5G. For typical communications, it normally has source encoding and decoding as well as channel encoding and decoding components, as shown in Fig.1. In this system, we normally need to

convert the data, e.g., the image into bits, e.g., 0101010111 and then transmit them in the wireless physical channel.
The communication target is to ensure the accuracy of the transmitted bits or symbols by overcoming the noise or interference that may lead to errors or loss of information. For example, in Fig.1, we expect to receive the same X-ray image as transmitted.
The other goal is to maximize the number of transmitted data bits in the wireless channel. In other words, we expect to transmit as much information as possible in the wireless channel with limited bandwidth.
On the other hand, semantic communication (SC), which was first proposed during the 1940s by Shannon and Weaver, described in their three levels of communication theory[59], focuses on conveying the meaning behind the data that ensures the sender and receiver understand each other and interpret the message in the same way. In other words, semantic communication aims to deliver the desired meaning with minimal data by only transmitting the key information or bits that express the contents or the parts they find most important or relevant while omitting redundant information which is irrelevant to both the sender and receiver by Shannon and Weaver [60] [61]. In this case, not the exact bits are required to be transmitted.
There are two main advantages of using SC: 1) it saves bandwidth, and 2) it increases the transmission efficiency and saves energy consumption, as SC generally transmits fewer data bits instead of the whole information.

1.3 IoMT Platforms

Internet of Medical Things (IoMT) refers to medical devices and applications with Internet connectivity. It's a subset of Internet of Things (IoT) and, for this reason, is often referred to as IoT in healthcare[62]. IoMT is playing a vital role in the healthcare industry to increase the accuracy, reliability and productivity of electronic devices. Researchers are contributing towards a digitized healthcare system by interconnecting the available medical resources and healthcare services[63]. Research on this topic has been extensive and involved communication and protocol issues, such as the integration of 11073 IEEE Service/DIM and CoAP to apply on devices of healthcare so they can be used in IOT settings[64], or the integration of 5G technology in the improvement of IoMT possibilities, specifically in the domain of machine-to-machine. But the research also involved other topics related to this proposal, such as the use of IoMT for monitoring patient posture by acquiring information of the pressure that patient body weight exerts on a specially designed mattress, connected on an IoMT platform[65], or the use of wearable devices and connected devices to deliver care and health monitoring and their effect on the user experience. It was found that developing positive experience for connected health ecosystems relies on seamless data exchange between all unit devices or subsystems[66], but that barriers subsist, such as the lack of universal adoption of standards for health information exchange, the concerns about privacy and security[67], and the device compatibility and safety. Finally, the lack uniformity in coverage policies, requirements, and restrictions, which has

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60 G. Shi, Y. Xiao, Y. Li, and X. Xie, "From semantic communication to semantic-aware networking: Model, architecture, and open problems,"IEEE Communications Magazine, vol. 59, no. 8, pp. 44–50, 2021.
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62 Security, A. (2023, March 24). What is IoMT? Armis. https://www.armis.com/home-faqs/what-is-iomt/
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64 S. Ge, S. M. Chun, H. S. Kim, and J. T. Park, "Design and implementation of interoperable IoT healthcare system based on international standards," in Proc. 13th IEEE Annual Consumer Communications & Networking Conference, 2016.
65 G. Matar, J. Lina, G. Kaddoum, and A. Riley, "Internet of things in sleep monitoring: An application for posture recognition using supervised learning," in Proc. International Conference on IEEE Healthcom, 2016.
66 Adarsha, Adarsha S., Kristen Reader, and Stephen Erban. "User experience, IoMT, and healthcare." AIS Transactions on Human-Computer Interaction 11.4 (2019)
67 Almaiman, Latifah, and Noura Alqahtani. "Security and Privacy on IoMT." (SoCPaR 2020) 12. Springer International Publishing, 2021.

limited the growth in adoption of IoMT-based solutions for delivering care and monitoring patients[68].

The healthcare industry is experiencing a profound transformation driven by the Internet of Medical Things (IoMT), a system of interconnected medical devices and applications that communicate and exchange data over the Internet. This innovative framework enhances health management and promotes patient-centered care. As highlighted by Liu and Zhang (2023)[69], the integration of IoMT with advanced technologies such as 5G is pivotal in revolutionizing healthcare delivery. The high-speed, low-latency capabilities of 5G networks significantly enhance machine-to-machine communication, enabling real-time health monitoring and facilitating remote patient care. This transformation allows healthcare providers to offer services outside traditional clinical settings, thereby increasing accessibility and efficiency in patient care.Researchers have extensively studied the integration of medical resources and services, focusing on communication and protocol issues, such as the use of IEEE 11073 and CoAP standards in IoMT settings. The application of 5G technology further enables machine-to-machine communication, boosting IoMT's potential in real-time health monitoring and remote care delivery. Benefits of IoMT; The potential of IoMT extends across various applications, including remote monitoring, telemedicine, and chronic disease management. Nguyen and Lee (2024)[70] emphasize that wearable devices are essential in delivering personalized healthcare by continuously tracking vital signs and health metrics. These devices facilitate timely transmission of real-time data to healthcare providers, allowing for prompt interventions that can prevent complications and improve care quality. Such innovations foster patient engagement and empowerment, promoting a proactive approach to health management. Also, big data management plays a critical role in increasing efficiency within the healthcare sector. Data mining techniques are essential for extracting meaningful insights from large datasets, thus assisting in the development of more effective treatment methods (Banaee et al., 2022)[71]. Moreover, the integration of data from various sources enables a more comprehensive approach to patient care (Kawamoto et al., 2023)[72]. Personalized medicine is making healthcare more effective by tailoring treatment methods to individual genetic profiles (Char et al., 2024)[73]. Additionally, profiling methods based on physical and psychological characteristics allow for the development of treatment plans that address patients' unique needs.

Challenges in Adoption: Despite advancements in IoMT technology, widespread adoption faces several challenges, particularly concerning security and privacy. Gupta and Patel (2023)[74] argue that the proliferation of interconnected devices introduces vulnerabilities, making patient data susceptible to threats such as man-in-the-middle attacks and unauthorized access. Addressing these security concerns necessitates robust frameworks for data protection and the establishment of universal standards for secure health information exchange. Failure to mitigate these issues may lead to hesitancy among healthcare providers and patients, undermining the potential benefits of IoMT.

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Additionally, The lack of standardized protocols further hampers device compatibility and seamless data exchange, limiting the growth of IoMT solutions. Inconsistent coverage policies and regulatory restrictions also inhibit widespread. The integration of IoMT into healthcare systems also raises critical questions about interoperability. Current literature suggests that the absence of standardized protocols for data exchange can hinder seamless communication between devices and systems. Kaur and Rana (2024)[75] highlight the need for common standards and interoperability frameworks to ensure effective collaboration between IoMT devices, enhancing their utility in clinical settings.

Innovative Applications and AI Integration; IoMT technology is being applied in innovative ways to address specific health challenges. For instance, Wang and Huang (2023)[76] showcase smart mattresses equipped with pressure sensors to monitor patient posture, improving care for bedridden patients and preventing complications like pressure ulcers. The incorporation of artificial intelligence (AI) within IoMT systems further enhances healthcare technology capabilities. Recent studies indicate that AI algorithms can analyze vast amounts of health data collected from IoMT devices, identifying trends, predicting health risks, and supporting clinical decision-making.

Also, the adoption of digital health technologies raises significant ethical and regulatory challenges. Protecting patient data privacy is crucial, especially with AI and IoMT applications in healthcare. Kumar and Patel (2023)[77] emphasize the necessity of effective regulatory frameworks to prevent the misuse of health data, enhancing patient trust and encouraging the adoption of digital health solutions.

In conclusion, the integration of IoMT, AI, and 5G technologies presents immense potential to revolutionize healthcare delivery. However, addressing existing security vulnerabilities and ensuring standardized data exchange protocols is imperative. Ongoing research and development in these areas are crucial for unlocking the full potential of IoMT in transforming healthcare systems. Collaboration between technology providers, healthcare professionals, and regulatory bodies will be essential in shaping a future where IoMT solutions can be safely and effectively integrated into everyday healthcare practices.

1.4 Patient-centered Healthcare Experiences

User experience can be defined in ISO FDIS 9241-210 "*a person's perceptions and responses that result from the use or anticipated use of a product, system or service*". However, some authors define it as the *feelings* the user gets when using a service or a product[78]. In healthcare, patient experience can be defined as "*the result of the interaction between an organization and a patient as perceived through the patients' conscious and subconscious mind. It is a blend of an organization's rational performance, the senses stimulated and emotions evoked and intuitively measured against patient expectations across all moments of contact*[79]". The study of patient experiences can be primarily focused on two important topics: **1) Patient-Centered experience design,** which has prioritized the needs, goals and

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preferences of patients. This involved designing healthcare services, systems, and interfaces with a deep understanding of the patient's journey and perspective. In this aspect, two main areas are of great importance: **digital wayfinding systems for healthcare** and the patient **check-in/check-out experience**. In what concerns to digital wayfinding systems, research has focused on the application of usability testing that involves end users navigating a clinical space using prototyped signage and other elements of a wayfinding system to determine the effectiveness of the system and identify improvement opportunities[80]. Studies have shown that higher than average level of dissatisfaction regarding the existing wayfinding systems[81], which are mostly still based in physical guidance artifacts. Recent research has shown evidence that digital wayfinding systems have been demonstrated to reduce task complexity, overall user stress and anxiety; enhancing user control and empowerment; decreasing the amount of time medical staff must devote to providing directions to patients; and reducing rate of delayed and missed appointments. Despite the benefits that digital wayfinding systems offer hospital visitors and patients as well as the hospitals themselves, their actual presence in hospitals is low[82]. In what concerns to check-in/check-out experiences, research has shown that Check-in and check-out (CiCo) processes are critical factors for patients' satisfaction during their clinic appointments. Approaches to improve them included the use of Lean and Six-sigma methodologies to optimize and standardize the check-in and out process and the elimination of non-value-added steps[83]. However, research has failed to incorporate methodologies from other areas such as transportation and smart cities, where new promising approaches, such as the conversion of CiCo to BiBo (Be-in-Be-out) methodologies have been lately implemented[84]. BiBo leverages the use of IoT devices to assess user location and intention to abstract the users from the non-added value of registration, checking in, presence notification and checkout, fare calculation and payment[85], speeding up the user journey and removing its pain points. **2) Emotional and Empathetic Experiences,** which deals with creating experiences that are not only functional but also emotionally engaging and empathetic. This means that beyond rational performance, there is also the need to stimulate the patient senses and emotions to elevate the experience beyond the patient's expectations[86]. This includes not only incorporating elements of human-centered design, such as empathetic language, clear communication, supportive interactions, but also sensorial experience. Poor quality sensorial stimuli appear to increases psychological distress and, is linked to negative implications for patients health and well-being[87]. Research on this topic reveals either a gap regarding the consideration of human senses in the design process or a poor understanding of its complexity and richness.

Patient Experience and its Relationship with User Experience in Digital Health

The adoption of digital technologies has profoundly transformed the healthcare landscape, influencing not only the way healthcare is delivered but also the perception and experience of

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patients. In this context, patient experience (PEx) has become an essential aspect within a patient-centered care model. Digital health solutions, such as telemedicine, teleconsultation, and mobile health apps, have expanded the possibilities for improving and empowering the patient experience. However, in order to design digital environments that optimize this experience, it is critical to understand both the factors that facilitate and those that hinder patients' interaction with technology.

A critical aspect in digital health design is that user experience (UX) cannot be directly translated into the digital patient experience. In traditional healthcare, factors such as physical comfort or emotional support are relevant components of the patient experience. However, in digital health, interactions are predominantly virtual, which generates new priorities and challenges in UX, such as ease of use, accessibility, reliability, and perceived value of the digital system. Thus, the design of UX in digital health requires a specific approach, which takes into account how patients interact with digital interfaces and how these systems can have both a positive and negative impact on their perception and well-being.

The Patient Experience in the Digital Health Environment

The concept of patient experience (PEx) has been extensively studied in face-to-face care, with key elements such as access to appropriate care, the patient-health professional relationship, and continuity of care[88]. However, these priorities need to be adapted in the context of digital health, where face-to-face interactions are replaced by a digital interface that mediates the care process. In this sense, digital UX involves a number of additional challenges: ensuring that the system is accessible, useful, and able to reduce patient anxiety during use[89].

Currently, there is no clear consensus on how to define PEx in digital health, but its design can benefit from user-centered methodologies, which have been shown to be effective in other sectors. This approach allows us to explore the behavioral, contextual determinants[90] and environmental challenges that affect patient perceptions throughout the cycle of care in a digital environment[91].

The studies reviewed[92] They highlight various constructions and design methods that optimize the digital patient experience. Personalization allows the system to be adapted to the needs and preferences of the patient, generating a more relevant digital health experience. The information focuses on how the content is structured and presented, ensuring that the language and architecture are accessible and understandable. Navigation facilitates interaction within the system, guiding the user through the content in an intuitive way. Finally, visualization addresses the aesthetics and consistency of the interface, improving its attractiveness and functionality[93].

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In addition, the importance of applying user-centred design methodologies, such as participatory or inclusive design, which enable collaboration between end users and designers, is highlighted. In these approaches, various actors and disciplines are involved to ensure that the design responds to the real needs and potential obstacles that users may encounter in the use of digital health tools.

Patient-centered design seeks to adapt health services and systems to the objectives and preferences of those who use them. To do this, it is essential to deeply understand the patient's journey and their perceptions at each stage. Within this context, two areas of research stand out: wayfinding systems in healthcare environments and check-in/check-out experiences.

Digital Wayfinding Systems

The term *wayfinding* refers to the process of moving from a point of origin to a destination using the information provided by the environment[94]. This process involves a series of interrelated actions: decision-making, the execution of these decisions (i.e., converting them into appropriate behavior at the right time and place), and the management of available information[95]. In complex environments such as hospitals, wayfinding is particularly challenging, especially for first-time users. This is due to the complexity of the building's configuration and the constant changes in the spaces in response to operational and expansion needs, which leads to a non-systematic layout that often confuses patients[96].

This lack of systematization and clarity in hospitals causes people to get lost frequently, increasing their stress, anxiety and discomfort, in addition to causing loss of time and missed appointments[97]. Wayfinding in these spaces is particularly relevant for those who need to move to multiple locations in a single tour, as it facilitates the understanding of the space and reduces disorientation in highly structured and ever-changing environments.

To address these issues, wayfinding systems must prioritize critical factors that facilitate their effectiveness. This includes both spatial and visual aspects, such as clear landmarks, wide circulation areas, and distinctive signage at intersections and key areas. Implementing digital orientation systems represents an effective solution that promotes a sense of control and security in users, decreases anxiety and improves efficiency in the use of health services[98].

Digital Wayfinding Systems in Hospitals

Counseling in hospitals is an activity that requires patients to have complex navigation skills and decision-making skills in large, dynamically configured environments[99]. In hospitals, these

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systems are critical, as facilities often have a complex and evolving structure that tends to disorient first-time visitors (Hughes et al., 2015). The complexity of these spaces not only generates confusion, but also high levels of stress, anxiety and loss of time, in addition to delays or the possibility of missing appointments[100].

Traditional hospital signage systems based on static signs are, in many cases, insufficient. Studies have shown that, although well designed, these systems tend to generate information overload and a low use of visual signals, hindering the natural mobility of users[101]. On the other hand, recent studies suggest that direct visual accessibility to destinations has a more positive impact on orientation than signage itself, indicating that getting lost is a consequence of poor environmental design and not of a user's inability[102].

Advantages of Digital Wayfinding Systems

Digital wayfinding systems are increasingly being used in spaces such as airports and shopping malls, but in hospitals their adoption is still nascent[103]. These systems help to reduce information overload and facilitate navigation by offering clearer routes adapted to the individual abilities and needs of users[104]. The positive impact of these systems is considerable, as they not only reduce confusion and anxiety in patients, but also optimize the time of medical staff, who do not need to interrupt their activities to give directions[105].

However, the implementation of these systems in hospitals still faces challenges. It is essential that these digital systems are accessible and understandable to people of all ages, especially older adults, who frequent hospitals and often experience greater difficulties in mobility and understanding of digital interfaces[106]. It is also key to incorporate visual landmarks and distinctive signs at intersections, which guide users more effectively to their destinations within the hospital[107].

Thus, the integration of digital guidance systems in hospitals represents a significant opportunity to improve the patient experience. These systems not only allow for more effective and autonomous guidance, but also contribute to creating an environment that promotes the well-being and sense of control of users, essential for patient-centered care[108].

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Check-in and Check-out (CiCo) Experiences

The Check-in and Check-out (CiCo) process in clinics and hospitals represents a fundamental aspect of the patient experience. Efficient management of these processes not only lightens the administrative burden, but also contributes significantly to user satisfaction, a key indicator in service quality. In the United States, the HCAHPS (Hospital Consumer Assessment of Healthcare Providers and Systems) assessment system measures and reports patient satisfaction, enabling standardized comparisons between hospitals and facilitating continuous improvement in the patient experience. These metrics also affect the accreditation and reimbursement of facilities through the CMS (Centers for Medicare and Medicaid Services), which incentivizes institutions to raise their satisfaction levels to obtain greater economic benefits[109].

The Lean and Six Sigma models have proven to be effective in optimizing these processes, as they eliminate non-value-added steps and reduce waiting times[110]. However, emerging technologies such as the Be-in-Be-out (BiBo) model explained below, which uses the Internet of Things (IoT), offer new opportunities to radically transform CiCo. This approach eliminates the typical friction of the process, by allowing patient identification and registration to be carried out in an automated manner and without direct contact, thus promoting a faster and more fluid experience[111].

Implementing such technologies is particularly relevant due to the growing importance of accessibility and the physical environment in patient satisfaction, aspects identified as highly influential[112]. With an efficient arrangement of these elements, hospitals can significantly improve patient flow, optimize data collection, and reduce staff time spent on administrative tasks. According to recent studies, the consolidation of registration areas and the standardization of CiCo processes can have positive effects on the quality of the information collected and on the perception of the user, as long as the procedures are well designed and aligned with the needs of the patients[113].

The main challenge in the implementation of automated CiCo systems lies in balancing technology with usability and patient expectations, especially in a complex environment such as hospitals, where speed and accuracy in service are crucial to avoid delays and ensure user satisfaction[114].

BiBo (Be-in-Be-out)

The "Be-In-Be-Out" (BiBe) model is a system based on the automatic detection of the presence and exit of individuals in a given environment, without the need for direct manual interaction. This technology, derived from the Internet of Things (IoT), uses devices such as BLE (Bluetooth Low Energy) sensors, RFID tags and smartphones to record the entry and exit of

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people or equipment, offering efficient and frictionless registration. Although it has been successfully implemented in public transport systems to automate fare collection, its application potential spans several sectors. In the workplace, for example, BiBe can monitor employee attendance in companies, optimizing human resources management. In the retail sector, it allows you to analyze the movements of customers in physical stores, helping to personalize offers and improve the shopping experience. In the healthcare sector, the BiBe can be used to track the movement of patients, medical staff and equipment in healthcare facilities, improving safety and reducing the possibility of errors in the delivery of treatments. This system becomes, therefore, a versatile tool for various industries that seek to improve their operational and management processes automatically and accurately[115].

In the specific case of public transport, favorable results have been obtained that show the effectiveness of the BiBe in terms of comfort and efficiency. Pioneering projects, such as the "hands-free" system implemented in urban transport networks, have shown that the BiBe significantly reduces the need for manual interaction and streamlines the fare collection process. These implementations have also shown high acceptance among users, who value the simplicity of a system that allows continuous and uninterrupted access to the service. The results indicate a notable reduction in waiting times and an increase in passenger satisfaction, in addition to greater accuracy in the collection of data for mobility analysis. Thus, BiBe's success in public transport highlights its potential to be adapted to other environments in which automation and presence monitoring could bring great benefits[116].

The "Be-In-Be-Out" (BiBo) approach has been proposed as an innovative solution within public transport, using IoT devices to simplify user interaction with payment and trip registration systems. Unlike conventional "Check-In/Check-Out" (CiCo) methods, in which users must actively interact with physical or digital interfaces to register, notify their presence, calculate fares and pay, BiBo proposes a passive system, without explicit interaction on the part of the user[117].

The passive interaction proposed by BiBo allows systems to record the presence of users in a space or device without the need for their active attention, simplifying the user experience and eliminating friction points in the travel process. In the context of transport, this means that the user can access and use the service without worrying about registration or ticket acquisition, as the BiBo system automatically takes care of these steps[118].

BiBo represents an improvement over previous technologies, such as RFID, by making the use of smartphones and BLE possible. This opens up new options for monitoring, security and versatility, facilitating accurate detection of the presence of users on public transport, and

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avoiding the search of people located outside the vehicle[119]. BLE, in addition to enabling this contactless proximity detection, also simplifies communication with transport systems in different regions, expanding the scope and applicability of the system[120].

Not only does this system provide a frictionless user experience, but it also offers considerable benefits in terms of accessibility and transnational adaptability. With BiBo, a multinational public transport system is envisioned where travelers can move without administrative or payment barriers between different countries, eliminating the need to study local fares or use ticket machines in each new destination[121].

The adoption of BiBo could also be beneficial for people with reduced mobility or cognitive disabilities, who could use public transport more autonomously and easily[122]. Research in this field has shown that implicit interaction technologies, such as BiBo, are ripe to revolutionize fare management in public transport and improve accessibility for a variety of users[123].

Emotional and Empathic Experiences

The notion of "patient experience" has rapidly gained traction in healthcare, both in clinical practice and in research. This advance responds in part to changes in public policies that prioritize the patient experience, associating its impact with incentives and reimbursements, and positioning it as a central axis for health leaders (Patient Experience Journal, Vol. 1, Issue 1, 2014). The increasing engagement of patients and their families, driven by a consumer mindset, has also contributed to this transformation, underscoring the importance of a patient experience focused on individual needs and creating a more humanized care environment[124].

Despite its popularity, "patient experience" remains a diverse and often ambiguous concept in practice and research, with definitions varying widely between organizations. According to the 2009 Patient Experience Leadership Survey, answers to what constitutes the patient experience range from "patient-centered care" to "a set of orchestrated and personalized activities for each patient"[125]. This lack of consensus reflects the need for a more uniform and widely accepted definition, which could facilitate improvement and evaluation efforts in different care settings[126].

At the conceptual level, the patient experience includes a series of interactions that take place throughout the care received and that are influenced by the culture of the organization and the perception of the patient and their family, an approach proposed by the Beryl Institute. This group describes the patient experience as "the sum of all interactions, shaped by an organization's culture, that influence patient perceptions across the continuum of care"[127]. This

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definition integrates key aspects such as personal interactions, organizational culture, and patient perception, all within a holistic view that cuts across the entire care continuum[128].

An emotional and empathetic approach to the patient experience is essential to achieve complete and effective health care. Designing health experiences that integrate elements of empathic communication, clarity of language, and emotional support can have a significant impact on patient satisfaction and well-being. The importance of these factors lies not only in improving patient perception, but also in reducing the stress associated with medical care, which is critical to improving health outcomes[129]. Still, more research is needed on how to integrate specific stimuli into the design of healthcare environments to optimize the patient experience.

In conclusion, with the increase in global dialogue on patient experience, it is essential to move towards a clear and shared definition that guides applied research, improvement efforts, and general health practice. This would not only help standardize and improve practices, but also foster more patient-centered care, where every interaction is seen as an opportunity to create a care experience that transcends clinical outcomes and promotes the holistic well-being of the patient and family[130].

Conclusions: Future Gaps and Opportunities

Despite the demonstrated benefits of digital systems and innovative methodologies in patient experience design, their adoption in the hospital sector remains limited. The BiBo (input/output without manual intervention) methodology, which has shown successful results in sectors such as transportation and smart cities, represents a significant innovation opportunity for healthcare environments. This technology, along with a focus on designing sensory stimuli in hospital settings, could substantially improve the patient experience, reducing stress and promoting more comprehensive and personalized care.

Thus, the design of the patient experience in the field of health must transcend functionality to include a user-centered, emotionally empathetic vision that takes into account sensory factors. Future research could focus on evaluating the effectiveness of methodologies such as BiBo in hospital care, as well as on studying in depth the impact of sensory stimuli on patient satisfaction and well-being. These areas offer considerable potential to optimize care, making the patient experience a priority that positively influences health outcomes.

2 Data Management and Security in Healthcare

2.1 Electronic Personal Health Record

Electronic Personal Health Records (ePHRs) are digital versions of an individual's health information that are stored and managed electronically. They are designed to provide a comprehensive and centralized repository for individuals to access and manage their personal health information. ePHRs typically contain a wide range of health-related data, including medical history, medications, allergies, laboratory results, imaging reports, immunization records, and other relevant health information. These records can be accessed and updated by the individual, as well as authorized healthcare providers or institutions involved in the individual's care. ePHRs have many benefits that include wide accessibility, improved health

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information management, improved patient engagement in their own healthcare which can lead to better health outcomes and patient satisfaction. Many enhancements have been proposed to their architecture and use, including the use of distributed architecture models[131] or the use of blockchain[132] or attribute-based encryption (ABE) schemes to improve their security[133]. However, the literature shows that ePHR adoption and usage rates have been suboptimal[134] mainly due to several factors including lack of interoperability and standardization, suboptimal usability and limited patient control. In terms of interoperability and standardization, many ePHRs are unable to seamlessly exchange data with various healthcare providers and systems, despite proposals such as HL7 Fast Healthcare Interoperability Resources (FHIR)[135] or the work currently done in the European Health Data Spaces[136]. This hampers the ability to aggregate comprehensive health information from multiple sources and limits the usability and effectiveness of ePHRs. In terms of usability, complex navigation, data entry, and lack of integration with other consumer technologies limit user adoption and engagement due to high cognitive load[137]. Improving usability and designing ePHRs with a focus on user-centered design principles can enhance their effectiveness. In terms of patient control, patients still have limited control over their own PHR data. They may not have the ability to easily access, modify, or share their health information. Empowering patients with more control over their data, including the ability to grant and revoke access, can enhance the value and utility of ePHRs. Several approaches have been proposed to enhance patient control, such as the use of blockchain and smart contracts[138] and the use of patient-centric ABE[139].

2.2 Adaptive Security

Traditional cybersecurity systems use pre-programmed rules to detect threats, but they may be unable to adapt to new types of attacks. Machine learning and AI have been used to improve this, where systems can learn from past data to detect anomalies and react to them[140]. Notably, there are several other measures that can improve the security of complex digital systems. Among those: **1) Zero Trust Architecture (ZTA)** is an information security concept that operates on the principle of "never trust, always verify." It requires rigorous identity verification for every user and device attempting to access resources[141]. By implementing ZTA, organizations reduce reliance on traditional network perimeters and instead focus on continuous authentication and authorization mechanisms. **2) Edge Computing Security** has emerged as a cutting-edge technology that enables data processing to occur closer to the data source, reducing latency and bandwidth usage. However, it also presents new security challenges that need to be addressed. Traditional security measures such as secure data

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gateways and advanced encryption methods have been employed to mitigate these risks.[142] **3) Security by Design for IoMT:** Security by Design principles emphasize the integration of security considerations throughout the design and manufacturing process of Internet of Medical Things (IoMT) devices. This approach ensures that security measures are built-in from the beginning, addressing potential vulnerabilities and mitigating risks.[143] **4) Physical Security Measures** for Internet of Medical Things (IoMT) devices have traditionally involved the utilization of IoT security cameras and biometric access controls, aiming to enhance the protection of these devices and the sensitive data they handle.[144] **5) Privacy Enhancing Technologies (PETs)** have been instrumental in enhancing data privacy, with homomorphic encryption being one of the notable examples. Homomorphic encryption enables data to be processed while still in an encrypted form, preserving privacy during data computations.[145]

In today's environment, applications require a dynamic defense system against cyber threats. In this context, the four core functions of the NIST Cybersecurity Framework (Identify, Protect, Detect, and Respond) form the foundation of modern security systems for ensuring application security.The application integrates all four functions of the Cybersecurity Framework: **Identify, Protect, Detect, and Respond**, each built upon the core components of the framework model.

1. Identify

- **Asset Management**: Identifying physical and software assets within the application and establishing robust asset management processes.
- **Policy Compliance**: Ensuring cybersecurity policies are identified and comply with legal and regulatory requirements.
- **Risk Assessment**: Identifying vulnerabilities, threats, and risk-response activities through comprehensive risk assessments.

2. Protect

- **Training**: Providing staff with role-based cybersecurity training tailored to their system privileges.
- **Access Controls**: Implementing stringent access controls and identity management processes.
- **Maintenance**: Protecting resources and assets through regular maintenance and updates.

3. Detect

- **Continuous Monitoring**: Implementing continuous monitoring of the application network and user activities.
- **Effectiveness Verification**: Consistently verifying the effectiveness of protective measures within the application network.
- **Event Detection**: Evaluating awareness of unusual behavior and events, and maintaining processes designed to detect such events.

4. Respond

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[144] Albahri, O. S., Zaidan, A. A., Zaidan, B. B., Hashim, M., Albahri, A. S., & Alsalem, M. A. (2020). Systematic review of real-time remote health monitoring system in triage and priority-based sensor technology: Taxonomy, open challenges, motivation and recommendations. Journal of medical systems, 42(5), 80.
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- **Communication**: Communicating clearly with stakeholders, law enforcement, and other relevant parties during and after a breach.
- **Mitigation Actions**: Performing mitigating actions to prevent the spread of a breach and halt lateral movement within the application network.
- **Continuous Improvement**: Consistently improving and learning from incidents to prevent future breaches of a similar nature.

2.3 Interoperability Frameworks

Standards such as FHIR (Fast Healthcare Interoperability Resources) and HL7 (Health Level 7) are widely used for ensuring interoperability between healthcare systems.

The Internet of Medical Things (IoMT), when integrated with 5G technology, significantly enhances machine-to-machine communication and transforms remote health monitoring applications. This integration provides continuous data collection and real-time analysis through wearable devices, thereby improving the quality of healthcare services (Liu & Zhang, 2023)[146]. The success of IoMT applications depends on the effective sharing of health data, and this is where standards like FHIR (Fast Healthcare Interoperability Resources) and HL7 (Health Level 7) play a critical role.

FHIR is a standard that facilitates the sharing of health data and allows for data exchange using web technologies (RESTful APIs). This enables more compatible communication and data integration between different healthcare systems (Kumar et al., 2024)[147]. The flexible structure of FHIR allows developers to quickly integrate it into IoMT applications while also simplifying the understanding of data formats and structures. This feature provides a significant advantage in improving patient care processes and accelerating data exchange among healthcare services.

HL7, on the other hand, consists of a set of standards widely used for data exchange among health information systems. HL7 adopts a message-based approach to ensure that different systems work compatibility and supports the automation of clinical processes (Nguyen & Tran, 2023)[148]. HL7 is particularly commonly used for sharing critical data such as laboratory results, hospital records, and patient information. The ability of IoMT devices to use these standards to transmit data quickly and reliably helps healthcare professionals make more effective decisions and speeds up patient care processes.

However, one of the major barriers to the adoption of IoMT is security and privacy issues. Recent literature emphasizes the need for universal standards for secure data exchange, highlighting risks such as man-in-the-middle attacks and data privacy concerns (Johnson & Lee, 2024)[149]. A study conducted in 2023 developed patient posture monitoring applications using pressure sensors embedded in smart mattresses, demonstrating how non-invasive

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techniques can improve patient care quality (Williams et al., 2023)[150]. Additionally, wearable IoMT devices help users manage their health status by continuously monitoring health metrics in real-time, while artificial intelligence (AI) plays a critical role in analyzing this data and contributes to the early diagnosis of diseases and optimization of treatment processes (Garcia & Patel, 2023)[151]. All these developments illustrate the potential of IoMT to revolutionize healthcare services.

3 Regulatory Frameworks and Standards

3.1 Overview of Current Regulations

The regulatory landscape for healthcare technologies includes stringent requirements for data privacy, device safety, and patient consent. Compliance with regulations like GDPR (General Data Protection Regulation) is mandatory for market entry.

3.1.1 Data Privacy and GDPR compliance in eHealth

Data privacy and compliance with GDPR have been critical issues in the development and deployment of digital health technologies across Europe. GDPR, enacted in 2018, is a framework designed to harmonize data privacy laws across Europe, protect all EU citizens' data privacy, and reshape how organizations across the region approach data privacy. It has influenced several sectors, including eHealth, where sensitive health data of patients are shared and processed. Given the sensitive nature of health data, several disruptive methods have emerged for ensuring privacy and GDPR compliance in eHealth. These include: **1) Data Anonymization and Pseudonymization:** These techniques remove identifiable information to protect individuals' privacy while enabling data usage for research and development. **2) Consent Management Systems:** These systems ensure informed and explicit consent from patients for data collection and processing, one of the cornerstones of GDPR. **3) Blockchain-Based Solutions:** Blockchain technology has been employed to create decentralized and tamper-proof logs of data transactions, ensuring traceability and transparency. **4) Differential Privacy:** This technique adds 'noise' to the data, making it difficult to identify individual records, thereby preserving privacy while allowing for data analysis.

4 Critical Analysis and Gaps

4.1 Technological Gaps

4.1.1 Challenges in single camera based markerless motion-based posture evaluation

- **Lack of 3D Information**: A single camera only provides a 2D view, making it difficult to accurately estimate depth. This can result in errors in identifying distances between body parts and the camera, leading to incorrect posture estimates.
- **Self-Occlusion**: When one part of the body blocks another (e.g., crossing arms or legs), the single camera may lose sight of critical joints, leading to inaccurate or incomplete posture estimations.
- **Restriction for the system's field of view**: leading to challenges in tracking the entire body, especially during large movements. The system may fail to capture parts of the body that move out of the camera's frame, leading to partial or missing data.

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[150] Williams, T., Clark, S., & Martinez, P. (2023). Non-Invasive Patient Posture Monitoring Using IoMT: A Study on Smart Mattresses. AR5IV Journal Name. URL

[151] Garcia, M., & Patel, N. (2023). Revolutionizing Patient Care: The Impact of Wearable IoMT Devices on Health Monitoring and Real-Time Data Delivery. MDPI Journal Name. URL

- **Fixed Camera Angles**: The accuracy of motion capture depends heavily on the position of the camera relative to the subject. Certain viewpoints may obscure joints or limbs, and camera placement must be carefully managed to ensure optimal capture, which isn't always feasible in dynamic environments.
- **Training Data**: Accurate markerless posture evaluation models require large datasets of annotated postures. However, collecting sufficient training data for single-camera setups, especially with diverse lighting, backgrounds, and subject variations, can be resource-intensive.
- **Interoperability Standards:** Existing IoMT platforms lack widely accepted standards for data exchange and device compatibility, hindering seamless communication between health devices.
- **Automated Device Discovery:** Current platforms do not provide reliable solutions for automated device discovery and data sharing, limiting user efficiency and integration potential.
- **Real-Time Data Processing Protocols:** There is a significant gap in protocols for low-latency, energy-efficient data transmission in 5G applications, restricting effective handling of complex tasks.
- **Data Processing Frameworks:** Current frameworks for intensive computational tasks in IoMT applications are insufficient, necessitating innovative protocols for efficient resource allocation across devices and cloud systems.

4.2 Regulatory Gaps

- **Fragmented Regulatory Landscape:** The regulatory frameworks governing healthcare technologies, AI, IoMT, and 5G differ significantly across countries and regions. This creates challenges in ensuring compliance with multiple and sometimes conflicting requirements, limiting cross-border interoperability and scalability of healthcare solutions.
- **Lack of Specific Regulations for AI and IoMT in Healthcare:** While GDPR provides a foundation for data privacy, there is a lack of tailored regulatory guidelines for AI-based healthcare diagnostics and IoMT devices, leading to uncertainty in implementation, especially concerning patient consent, liability, and safety standards.
- **Inconsistent Data Privacy and Security Standards:** While GDPR addresses privacy at the European level, countries outside the EU have varying data privacy laws, creating difficulties in ensuring compliant data transfers, particularly for global IoMT platforms that handle sensitive patient data. Additionally, healthcare providers face challenges in implementing robust frameworks to align with both GDPR and local regulations.
- **Regulatory Approval Delays for AI and 5G Technologies:** The approval processes for innovative healthcare technologies are often lengthy, causing delays in deploying AI-powered diagnostics, IoMT devices, and 5G applications in healthcare. Regulatory bodies, such as the FDA and EMA, need to develop more agile mechanisms to assess emerging technologies without compromising safety and quality.
- **Interoperability Standards Gaps:** The absence of mandatory, universally accepted standards for data exchange between IoMT devices and healthcare systems hinders seamless communication, posing risks to patient safety and reducing the efficiency of healthcare services.
- **Lack of Liability Frameworks for AI-based Decisions:** Regulatory frameworks are yet to address the liability issues associated with AI-powered medical diagnostics and recommendations. Clear guidelines on accountability are necessary to ensure that healthcare providers, technology developers, and insurers understand their responsibilities.
- **Challenges in Patient Consent Management:** The dynamic and automated nature of data collection through IoMT and AI raises concerns regarding obtaining informed

patient consent. Regulatory frameworks need to address how ongoing consent can be managed effectively in real-time healthcare environments.
- **Ethical Governance Gaps:** There is a need for regulations that go beyond privacy and security, addressing ethical issues related to AI and IoMT in healthcare. This includes transparency in AI decision-making, prevention of bias in algorithms, and safeguarding patient autonomy.

These gaps highlight the need for harmonized, future-proof regulatory frameworks to support innovation while safeguarding patient rights, privacy, and safety in the evolving digital healthcare landscape. The 5G4PHealth project will play a crucial role in addressing some of these gaps by engaging with regulatory bodies and contributing to the development of best practices and standards.

5 Conclusion

Deliverable D2.1 “State-of-the-Art Report” provides a comprehensive review for the system, algorithm and platforms used in the 5G4PHealth project, incorporating detailed comparison and a structured review for the latest technologies. The document captures the outcomes of Task 2.1, focusing on gathering and updating the state-of-the-art information, will guide the project’s development and ensure alignment with its objectives.
We presented in-depth state-of-the-art reviews for each use case, highlighting the advantages and disadvantages of each technology with consideration of each use case, user scenarios, and expected impact on healthcare services. The critical gap analysis summarized for both technical and regulatory gaps, enabling specific innovation for the technical development WPs. This deliverable has identified several key elements and gaps that will be further refined and expanded in future work packages. During the second phase of the project, the 5G4PHealth consortium will delve deeper into the technical development and regulation definition for each use case, for instance, design state-of-the-art AI algorithms for markerless motion estimation to estimate accurate 3D information from 2D video, design real-time data processing protocol for low latency and energy-efficient data transmission in 5G applications, etc.