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Master Program in Information Management

PATIENT RELATIONSHIP MANAGEMENT (PRM) AND AI

THE ROLE OF AFFECTIVE COMPUTING

Mariana Alves Carreiro

Dissertation presented as partial requirement for obtaining the Master's degree in Information Management

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PATIENT RELATIONSHIP MANAGEMENT (PRM) AND AI: THE ROLE OF AFFECTIVE COMPUTING

by

Mariana Alves Carreiro

Dissertation presented as partial requirement for obtaining the Master's degree in Information Management, with a specialization in Knowledge Management and Business Intelligence

Supervisor: Vítor Duarte dos Santos, PhD.

November 2022

ACKNOWLEDGEMENTS

Without the cooperation, work, and supportive commitment of a select group of significant individuals, for whom I am eternally grateful, this dissertation would not have been possible.

For his availability and assistance in helping me write and revise this dissertation, Vítor Duarte dos Santos, PhD, has been a great help to me.

I would also like to thank Dr. Tiago Harper Maia, Maria João Veiga and Lorena Falcão Lima for their availability, knowledge and contribution to the development of this dissertation.

Lastly, my family and friends, whose confidence in me kept my spirits and motivation high throughout this process, deserves a final mention.

ABSTRACT

Artificial Intelligence (AI) has been praised as the next big thing in the computing revolution, and it's been touted as a game-changer in a variety of fields, including healthcare. The increasing popularity of this technology is driving early adoption and leading to a lack of consideration of the patient perspective in its use, bringing new sources of distrust that come from the absence of human attributes.

This study aims to address this problem by presenting a strategy in the area of affective computing that will combat this absence of empathy experienced by the patient during a medical process. To reach this goal, a Design Science Research Methodology will be followed. A preliminary literature study had already been completed, and the research topic and objectives had been established. In addition, to apply the artifact developments, a bot will be built and evaluated by a set of users.

The increased awareness of these AI systems will, expectedly, stimulate their use. By adding new research into the affective computing field, it is also expected to contribute to the digital healthcare evolution and to encourage further scientific progress in this area.

KEYWORDS

Artificial Intelligence; Affective Computing; Healthcare; Patient Relationship Management; Design Science Research

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LIST OF ABBREVIATIONS

AC, Affective Computing

AI, Artificial Intelligence

AmI, Medical Informatics

ASR, Automatic Speech Recognition

CDSS, Clinical Decision Support Systems

CRM, Customer Relationship Management

DSR, Design Science Research

DSRM, Design Science Research Methodology

DSRP, Design Science Research Process

EHR, Electronic Health Records

ESSEC, École Supérieure des Sciences Économiques et Commerciales

HCI, Human-Computer Interaction

HIMSS, Healthcare Information and Management Systems Society

HIS, Hospital Information System

IMEI, International Mobile Equipment Identity

IT, Information Technology

IUI, Intelligent User Interfaces

MAC, Media Access Control

PRM, Patient Relationship Management

1. INTRODUCTION

1.1. Background and Problem Identification

Artificial Intelligence (AI) has been growing substantially over the last decades and it is becoming increasingly common to find its use in our everyday lives. It has already had an impact on people's lives, businesses, and political processes (World Economic Forum, 2020).

AI is defined as a system's ability to accurately understand external input, learn from it, and apply what it has learned to achieve specific objectives and tasks through flexible adaptation. (Kaplan & Haenlein, 2018).

AI has already changed the game in a variety of industries by facilitating the capture and organizing of data in a variety of ways. One of the most common examples is in the healthcare sector, where AI has already proven to be a huge success, with robotics assisting doctors with surgery, administrative tasks, image analysis, drug discovery, and also assisting clinicians in diagnosis, therapeutic decision-making, and outcome prediction (Ramesh et al., 2004).

Due to the significantly increased computing capacity of current computers and the large amount of digital data available for gathering and exploitation (Mesk et al., 2017), interest and achievements in medical AI applications have exploded in recent years.

Major changes in healthcare procedures and instruments have resulted from this technology disruption. It is regarded as a significant and influential process that has already had a significant impact on present health care and health systems and is projected to have an even greater impact on health care and health care delivery in the future (Ricciardi et al., 2019). Many goods and procedures have been enhanced and made more user-friendly. These intelligent technologies can be used to increase the efficiency and accessibility of existing resources, allowing them to serve more patients while also improving results and lowering costs (IANS, 2017).

AI approaches have sent shockwaves through the industry in response to these breakthroughs, igniting a heated debate about whether AI doctors would eventually replace human doctors. Some research studies have already shown that AI can perform as well as or better than humans at crucial healthcare activities including disease diagnosis (Davenport & Kalakota, 2019). It has demonstrated demonstrable benefits, playing a critical role in reducing errors caused by human error (Sunarti et al., 2020).

According to many studies, the effectiveness of integrating health information technology (HIT) will determine the healthcare industry's success and survival. In addition to delivering high-quality medical services and addressing patient requirements, consumer e-health, patient engagement, and patient-centric care all play important roles (Baashar et al., 2020).

1.2. MOTIVATION

There is a valid concern that as medicine becomes more data-driven, clinicians will lose sight of the important and intimate relationship, the human touch, with their patients (Topol et al., 2015).

Initial trust is necessary to ensure that new technology gets adopted. A user's first impression influences trust, which is formed based on that person's personality and institutional indications (Choudhury, 2020). Emotional states can be expressed by speech, facial expression, and other physiological representations, according to the literature (Lisetti & Schiano, 2000).

Fewer emotive clues flow through the communication process as means of communication and freedom of expression are reduced. As a result, the affective assessment may be prone to meaning misinterpretation and deception (Lisetti & LeRouge, 2004).

Especially in an area as sensitive as health, the way information is passed on to the patient is crucial to their experience. That is why it is critical to deliver services that meet both expectations. AI systems are also being applied in the healthcare sector to enhance the patient experience, patient care, and provide support to physicians through the use of AI assistants (Basu et al., 2020).

It's becoming more typical for patients to have direct access to algorithmic counsel. (Fraser et al., 2018). Due to its genesis, the interface can convey to the user a certain impersonality and coldness that can be perceived as a lack of empathy or solidarity. As a recent study has shown, patients are not ready for fully automated care (Tran, Riveros & Ravaud, 2019). Therefore, the patient perspective needs to be taken into consideration when developing AI-enabled health services (Nadarzynski et al., 2019).

Facing the interpretations that a patient may draw from the interface platform rather than human contact, there is a need to explore and clarify how health emotion drives patients' intention to continue to use patient portals (Luneski et al., 2010). The user approaching a device is not purely interested in what the device does, but rather how the device makes them feel: the developer must remember that the application is developed focusing on the customer and is designed to satisfy all their needs (Kairy et al., 2013).

1.3. Study Objectives

This research proposal aims to present a strategy in the area of affective computing to enable the creation of greater empathy between health support AI systems and users. It is understanding how its usage could optimize and support the patient care journey, enabling the effective flow of information, and increasing patient engagement.

To achieve this goal, the following intermediate objectives were defined:

- Study the importance of empathy and familiarity in patient relationship management.
- Make a scientific literature review about affective computing and other crucial fields to the study.
- Propose a strategy that improves the relationship between patients and AI healthcare services.
- Build the bot with the artifact concepts.
- Evaluate the strategy proposed using expert analysis.

1.4. Study Relevance and Importance

AI is being more widely used in medicine and healthcare. Providers that want to grow their services to rural places without having to relocate or enlarge their practice's footprint can use telehealth (Kruse et al., 2017). An increase of this technology adopters is expected, as a consequent growth of the market.

As technology finds its way into almost every aspect of human life, the questions of its ability to understand, help treat, develop, and impact the human psyche will continue to grow (Daily et al., 2017). Affective Computing (AC) enables investigation and understanding of the relationship between human emotions and health as well as the application of assistive and useful technologies in the medical domain (Luneski et al., 2010).

Therefore, due to its practical application, this study will not only contribute to the improvement of patient perception and experience, but to others such as hospitals, clinics, and health centres, as they can have a better understanding of how the implementation of affective computing can contribute to the patient relationship.

This study also aims to contribute to developing scientific knowledge that allows better implementation of patient interface systems in order to increase patient enrolment and target this technology to patients according to their characteristics to encourage ongoing engagement and overall satisfaction.

Moreover, as a scientific study, it extends the state of the art on the use of affective computing. Although this research study focuses on its application in the healthcare sector, as this is still an under-explored topic, will allow its generalization to other industries.

Finally, it brings a new strategy model to the scientific community that can be used by other authors. It is also expected to publish the research results in an article in an index scientific conference, encouraging further study on the topic.

2. METHODOLOGY

According to the proposal of producing a strategy in the area of affective computing to enable the creation of greater empathy between health support AI systems and users, the research output of this study is considered as an artifact. The artifact should be useful in resolving a previously unsolvable and significant business challenge (Hevner et al., 2004). These artifacts can be classified into five categories from a product standpoint: constructions, models, techniques, instantiations, and theories (Bucher & Winter, 2008).

Therefore, the Design Science Research Methodology (DSRM) seems to be the most appropriated for this study (March & Smith, 1995). As DSR focuses on artifacts' possibility to make useful contributions to the technology world, this will be the methodology used in the development of this solution.

2.1. DESIGN SCIENCE RESEARCH

The other half of the IS research cycle, design science, generates and analyzes IT artifacts aimed at resolving organizational problems. Since it is a problem-solving paradigm that attempts to generate an artifact or solution to a specific problem, it starts by identifying business needs and consequently arrives at finding solutions to organizational problems (Hevner et al., 2004). Design activities comprise processes of "build" and evaluate", usually after multiple iterations. During a DSR study, a variety of research methods are applied, including interviews, surveys, literature reviews, or focus groups (vom Brocke et al., 2020).

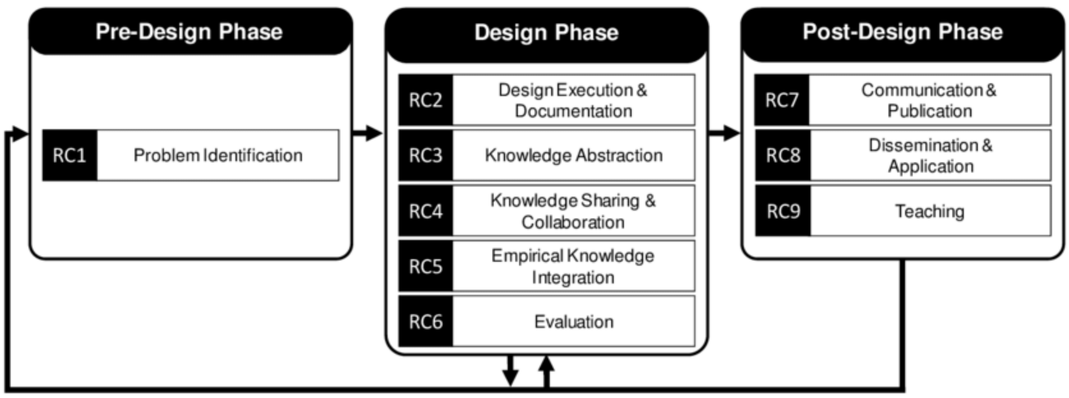

Figure 1 - DSR Methodology Model Phases (Adapted from Peffers et al., 2008).

According to Peffers et al. (2008), this technique adds to the field of Information Systems research by offering a widely acknowledged framework for doing Design Science research and a mental model for presenting it. If the design science research process (DSRP) is compatible with previous literature, an exemplar case that is relevant and flexible enough to enable DSR in Information Systems will be produced (Peffers et al., 2006). Since this is a project that aims to push the boundaries of knowledge through the design of a new and innovative artifact, it aligns with the objectives of a DSR project.

Taking as the basis of this research to give answers to a current existing problem, it meets what is recognized by vom Brocke et al. (2020) as the starting point of a DSR project, the analysis of the business environment and the specific needs that need to be addressed.

For this research, it will be followed the Hevner et al. (2004) process defined in six steps by Peffers et al. (2008) as illustrated in Figure 2: problem identification and motivation, definition of the objectives for a solution, design and development, demonstration, evaluation, and communication. A brief description of each DSR activity follows.

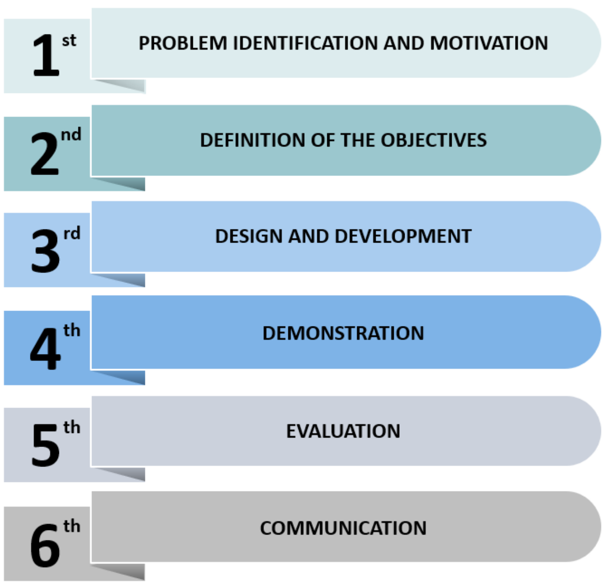

Figure 2 - DSR Methodology (Adapted from Peffers et al., 2008).

2.1.1. Problem identification and motivation

This is the initial action, which outlines the research topic in detail and justifies the importance of a solution. Justifying the value of a solution serves two purposes: it drives the researcher and the research audience to pursue the solution, and it allows the audience to appreciate the researcher's knowledge of the problem. This task necessitates awareness of the current condition of the problem and the significance of its resolution.

2.1.2. Definition of the objectives

The problem definition and knowledge of what is conceivable and doable can be used to infer the goals of a solution. The goals can be quantitative or qualitative in nature. The objectives should be logically deduced from the problem description.

2.1.3. Design and development

In this phase is the creation of the artifact. A DSR artifact can theoretically be any constructed thing that incorporates a research contribution. This activity entails identifying the desired functionality and architecture of the artifact, as well as building the artifact itself.

2.1.4. Demonstration

This activity explains how the artifact can be used to address one or more problems. This could include using it in experiments, simulations, case studies, proofs, or other relevant activities.

2.1.5. Evaluation

The evaluation assesses how well the artifact contributes to a problem-solving solution. This activity entails comparing a solution's objectives to actual observable results from the artifact's use in context. Evaluation can take different shapes depending on the nature of the problem and the artifact. At the conclusion of this activity, the researchers can choose whether to return to step three to increase the artifact's effectiveness, or to go on to communication and leave further improvement to future initiatives.

2.1.6. Communication

The relevant stakeholders are informed about all parts of the challenge and the intended artifact. Depending on the research goals and the audience, such as practicing professionals, appropriate modes of communication are used.

2.2 Research Strategy

Following the methodology presented above, the structure of this research will come out of the following stages.

First, a literature review will be performed in other to overview the state of the art of some of the most important concepts to the study, as Affective Computing, Emotions, AI. Additionally, an overview of the current technology used in the healthcare sector will be made. The information collected in this phase will provide the necessary knowledge to identify and define the existing problem.

In the second step, it is necessary to define and identify the objectives, which can be qualitative or quantitative. The main requirements of the research's artifact will be specified so the next stage has the necessary information gathered to build the artifact.

Therefore, the design and development of the artifact that will solve the research problem will be conducted. This activity includes determining the artifact's desired functionality and its architecture and then creating the actual artifact.

The demonstration of the use of the artifact will be done in the fourth step, and for it, a bot will be constructed. This bot will allow the implementation of the concepts developed so that in the next phase it can be evaluated by a group of users.

Once the evaluation phase is concluded, a presentation and further paper proposal will be performed in the communication stage, to understand how effective this solution is and gather more feedback on its performance (Hevner et al., 2004). The main limitations of the artifact will be analysed and suitable for future research.

3. LITERATURE REVIEW

Before moving on to the strategic model, there was a need to explore the theoretical background of these topics to understand the evolution of the concepts. This dissertation has two main areas involved, patient relationship management and affective computing. Both subjects are addressed in this section, detailing within each the relevant sub-topics for the research.

3.1. PATIENT RELATIONSHIP MANAGEMENT

3.1.1. Concepts

Patient Relationship Management (PRM) is derived from Customer Relationship Management (CRM) applied to the health sector. PRM is a system design strategy said to have the potential to increase patient satisfaction and reduce healthcare costs (Vardasca & Martins, 2011).

We can define PRM as the set of planning, delegation of tasks, decision making and every other service that aim to maintain and improve the relationship between patients and health services, whether with hospitals, pharmacies, health centers or even between services as public health system and pharmaceutical industry, with the goal of the best possible delivery of patient services and the efficient use of resources while supported by information and communication technologies. The focus of the healthcare organization shifts to understanding and responding to the needs of the patient (Kumar et al., 2017).

In 2012, one of the goals considered a priority by the World Health Organization was already the optimization of the patients-doctors relationship (Santus et al., 2012). The same year, a survey conducted by BearingPoint and ESSEC, confirmed that it is a growing concern for hospitals to meet patients' expectations regarding the experience of the hospital process, and acknowledged the importance that good PRM practices have in improving effectiveness and efficiency of the healthcare process. At the same time, while many hospitals recognize its benefits, progress is constrained by a combination of factors ranging from legacy technology to resistance to change (BearingPoint & ESSEC, 2012).

CRM for healthcare is a way to learn about patients, improve communication, construct honest interactions (Benz & Paddison, 2004), build deeper therapeutic alliances between providers and patients, track patient outcomes (Poku et al., 2016) and make necessary adjustments.

In 2015, HIMSS prepared a study that confirmed that an efficient system can help health professionals approach the development of outreach strategically, assisting them automatically target specific segments of patients or referral agencies. A more personalized approach to patient treatment can improve patient care. A follow-up treatment system appears to be a tool to build and sustain clearer communication with patients, rather than just a technological solution (Oinas-Kukkonen et al., 2008). By extracting the value from existing relationships, the cost of marketing turns out to be much lower than the cost of trying to attract new relationships. This also assists in building significant relationships by focused communication that increases repeat business and positive word-of-mouth, leading to new associations (Rowe, 2015).

The practical application of this concept has evolved over the years, starting from patient discrete service improvements, through more customer focus, to maximizing the patient's overall "customer experience" in a meaningful and measurable way (BearingPoint & ESSEC, 2012). Its implications include screening patient information from exercise and diet data to family history, to allergies, to information on past diagnoses. The desire is that this information can also be edited or added to by the patient, empowering them to provide and seek information (Vardasca & Martins, 2011).

This depth of customization is a vital success factor in the healthcare industry and serves as an additional option for healthcare professionals to use information systems to optimize the quality of care they provide (Siau, 2003). Failure to establish this type of relationship with patients will result in distrust and dissatisfaction, which will lead to patients switching healthcare providers (Baashar et al., 2016).

3.1.2. Empathy and Patient Satisfaction

The notion of "empathy" has a long historical background marked by ambiguity. A review of the literature reveals that researchers disagree more than agree on the definition of empathy (Hojat, 2007). Due to conceptual ambiguity, empathy has been defined as an "elusive" concept (Basch, 1983), a concept that is difficult to define and challenging to measure (Kestenbaum et al., 1989).

During the 1990s, there was a new wave of research about emotion's role in several areas, such as psychology (e.g. Ellsworth and Scherer, 2003), neurology (e.g. LeDoux, 1996), medicine (e.g. Damasio, 1995), and sociology (e.g. Katz, 1999). Prior, emotions had been considered a low-status research topic, and investigators had mainly focused on how emotion intersected with our rational thinking (Höök, 2014).

With this new wave of research, a new role was assigned to emotion. Defined as the sharing of the other person's subjective experience (Campbell & Babrow, 2004), empathy has been considered as the ability to understand and experience the thoughts and emotions of interaction partners (Davis, 1983; Eisenberg & Miller, 1987). Two sides, cognitive and affective empathy, are frequently distinguished (Davis et al., 1987). Cognitive empathy describes the capacity to cognitively understand the reactions and perspective of others. Affective empathy is a conceptual response that is coherent with the emotion of an interaction partner (Davis et al., 1987). Kim et al. (2004) distinguished between these two forms and concluded that patients were much more influenced by affective empathy (Kim et al., 2004).

Empathy makes it possible to experience both the positive and negative feelings of others, we feel happy when we share the joy of others, and we share the feel of suffering when we resonate with someone in pain (Singer & Klimecki, 2014). The function of empathy is not to label emotional states, but rather to recognize the feeling of experiencing something. That is why empathy is necessary, even when it is obvious which emotional label applies to a patient (Halpern, 2003).

In the relationship between physician and patient, empathy is also a key characteristic. Several studies show that there is a link between empathic relationships and clinical outcomes (Loureiro et al., 2011). Patients want genuine empathy from doctors, and doctors want to provide it (Bertakis el al., 1991). The benefits of clinical empathy have been proven to include increased patient satisfaction (Weng et al., 2011). It is considered important and positive to help patients, empirical research on the topic has grown quickly (Pedersen, 2009).

In 2015, Derksen and his colleagues reported that in a hospital situation, both the non-verbal and verbal behaviours of the patient are valued, in addition to being attentive to the signs, perspective the patient's thoughts and feelings (Derksen et al., 2015). Verbal communication involved phrases and expressions used by the doctor to convey to the patient that he understood his concerns and was committed to helping him. Nonverbal communication included touch, tone of voice, eye contact, and physical space (Sanders et al., 2021).

To work effectively, all components of clinical empathy should be employed together. There is a well-established link between healthcare practitioners' empathy and increased patient adherence, satisfaction, and treatment outcomes. Furthermore, empathy is linked to healthcare practitioners' professional satisfaction (Ratka, 2018). Clinical communication is assumed to be similar to a therapeutic relationship, since it includes communicative acts such as active listening and addressing patients' concerns (Roter & Hall, 2006). A physician's communication style and attention to patients' symptoms are crucial to improving the care experience (Mehra & Mishra, 2021) and can impact patient satisfaction (Smajdor et al., 2011).

Patient satisfaction is one of the most relevant parts of evaluating the quality of healthcare. In recent decades, patient satisfaction measurement systems have been gradually developed, differing in structure and complexity in several respects (Jennings et al., 2005). Patient satisfaction allows measuring the consistency between the patient's expectations, preferences and the healthcare provided (Gavurova et al., 2020). In recent years, several studies have documented the valuable possibility of improving the quality of healthcare services by increasing patient satisfaction. Bjertnaes et al. underlined the importance of including in this evaluation of health services not only the patients' satisfaction but also their expectations (Bjertnaes et al., 2011).

Last year, a study conducted by Gavurova et al., showed that the most relevant factor in patients' satisfaction with hospital care comes from their satisfaction with healthcare professionals, namely doctors, nurses, and other staff (Gavurova et al., 2021). Increased pressure for greater efficiency of healthcare facilities, along with the sustainability of healthcare systems, will also set greater requirements on patients' healthcare and impact their loyalty to healthcare services.

3.1.3. IT Role

The continuous increase in the volume of medical information has led hospitals to face a critical question, which is how to use information technology to handle large amounts of customer data and thereby improve the quality of their services (Khoshraftar et al., 2011). The use of information technology has emerged as a necessary condition for CRM implementation. An effective CRM demands a synergistic integration of an organization's strategy, technology, and people (Reddy & Acharyulu, 2002). Hospital CRMS need to be built on top of the Hospital Information System (HIS). HIS is defined as the subsystem of a hospital, integrating the information processing systems as well as the technical factors associated with its information managing functions (Haux et al., 2003). In 2012, Chen and Hsiao considered HIS as an integrated information system with a key role in supporting hospital activities using appropriate hospital information technology (Chen & Hsiao, 2012), this tool integrates information generated from medical acts, such as electronic health records (EHR), clinical decision support systems (CDSS), and telemedicine (Hung et al., 2009).

Given the importance of this information system, Vardasca and Martins suggested that the data it records should then be used by a PRM system to strengthen and maintain the relationship between the hospitals and patient. Since most of the data required for PRM comes from HIS, the integration of these two components maximizes the potential use of PRM (Vardasca & Martins, 2011). The purpose of PRM tools is to enable partner managers, as well as doctors, nurses, and other support teams, to remove redundant steps from their workflow and optimize, often by automating, essential tasks. This empowers hospital departments to achieve more in less time, while keeping their systems efficient and more productive.

There are several types of healthcare PRM IT solutions, which include: enabling patients to securely fill out pre-visit forms electronically at home to minimize their time in the clinic; enabling patients to request appointments on demand and pay their bills online (Poku et al., 2016); sharing educational and sales enablement resources; multiple communication channels that allows the service to be more responsive to the patients' needs and requests (Monem et al., 2011).

3.1.4. The IT Impersonality issue

However, while the governing bodies decide what features are indispensable for AI systems, they should also keep in mind that these systems will not succeed as a technology without the trust and acceptance from clinicians and patients (Choudhury, 2020). Concerns include the possibility of bias, lack of transparency, scalability, data integration and security, reliability, privacy, and ethics of aggregated digital data (Cath, 2018). In addition, variations in computer literacy or technical skills, divergences in patient attitudes towards electronic communication with providers are also factors that contribute to patients' distrust in implementing these technological resources (Goel et al., 2011).

A study conducted in 2008 by Greenhalgh et al, organized by 103 individual semi-structured interviews and seven focus groups, collected information to document the views of patients and the public towards the summary care record, verified that many respondents preferred to discuss their health issues with their own general practitioner or nurse instead of accessing their health data digitally. Some people pointed out that the digital platform would provide dispassionate information. Others feared that diagnosis could lend false objectivity to assessments, especially of the scope of a person's mental state (Greenhalgh et al., 2008). This vision of the patient is especially applicable in cases where the information to be passed on may contain bad news or abnormal results. In these cases, the way in which information is communicated is considered crucial by patients, and the majority of them prefer health professionals to be the transmitters of those cases (Pyper et al., 2004).

In 2019, a study conducted by Lau & Staccini to synthesize the state of the art during the previous year in consumer health informatics, found no eligible published articles reporting AI applications designed specifically for patients or consumers, nor literature eliciting patient and consumer input on AI (Lau & Staccini, 2019). There is a lot of information on how this technology facilitates and contributes to the evolution of medicine, but not enough investigations about the impact on its users, there is a lack of direction and evidence on how AI would benefit whether consumers or patients.

In 2020, a study published in the journal Frontiers in Medicine reported another common concern related to the use of AI. This was about compromising the doctor-patient relationship, pointing those consultations could become more sterile, with no face-to-face time with the doctor and less time for doubts. Respondents also feared that doctors would be tempted to rely so heavily on the AI-based algorithm that they would lose their diagnostic knowledge and skills. This would limit their ability to classify injuries without the support system, as well as their ability to detect obvious errors or malfunctions in the algorithm itself, resulting in deliberate technical glitches or manipulation by hackers. More recognizable issues were the lack of traceability of the default algorithm and the lack of transparency of the implemented system. In addition, they highlighted the risk of inequality of opportunity posed by potentially high costs not covered by standard health insurance (Jutzi et al., 2020).

3.1.5. Challenges and Opportunities

The importance of data transparency in clinical trials has long been debated, since it aids in the resolution of a variety of challenges. Transparency of data can aid in the development of trust and confidence among trial participants. It also aids researchers in avoiding unnecessary trial repetition, particularly when the results of previous studies have suggested that the substance is potentially dangerous. According to a cross-sectional study published in the British Medical Journal in 2021, 88% of over 20,000 mobile health (mHealth) apps accessible on the Google Play marketplace contained code that had the ability to collect user data. The majority of the information gathered by mHealth apps included the user's location, contact information, and device identifiers. The apps had access to international mobile equipment identity (IMEI), which is used to identify fingerprints on phones, and media access control (MAC), which identifies the network interface in the user's device (McKeon, 2021).

Moreover, engaging patients in their own healthcare is crucial for improving clinical results, increasing patient satisfaction, and generating economic revenue. Newer tools and technology that enable two-way communication are required. Promoting and speeding direct-to-consumer advertising, in which firms retain control over message delivery but media loops are closed for increased impact (Sharma, 2015).

3.2. AFFECTIVE COMPUTING

3.2.1. Concepts

Since the early 1990s, basic neural networks have been used in medicine to interpret electrocardiograms, diagnose myocardial infarction, and forecast the length of stay in an intensive care unit after cardiac surgery. Image analysis, text recognition, pharmacological activity design, and gene mutation expression prediction are among the scientific uses of AI that have grown (Miller & Brown, 2018).

Rosalind Picard is the person who is credited with pioneering the research in the branch of computer science known as affective computing. Her first book on this subject, *Affective Computing*, describes the important role of emotions in artificial intelligence, the vital role that communication of human emotions plays in relationships between people, and the potential impacts of emotion recognition by robots and wearable computers. She viewed affect recognition as a dynamic pattern recognition challenge, and she sought to use machine learning or neural network methods to represent an individual's or group of persons' affective states or a blend of such states. She advocated a "affective symmetry" in the manifestation of recognized affective emotions.

Affective computing defined as an emerging field, with increasing results mainly in facial expression recognition and synthesis, and voice inflection synthesis (Picard, 1995). Also known as the artificial intelligence of emotion, is an emergent technology in which computers and systems can identify, process, and simulate human feelings and emotions. It is considered an interdisciplinary field because it leverages computer and cognitive science, and psychology. (Dilmegani, 2021). The problem with affective computing boils down to this: We can't measure cognitive influences currently since they rely on self-reports that are likely to be very variable, and no one can read your mind (yet). We can, however, quantify physiological reactions (facial expression, for example) that frequently occur during emotional expression (Picard, 1995).

Affective computing solutions that operate with photos employ the following strategies to normalize face expressions: Face geometry (e.g. locations of mouth, eyes and nose) can be calculated after the face is extracted from the backdrop. Face emotions can be normalized using facial geometry, removing the effect of head rotations and other head movements (Dilmegani, 2021).

The goal is to establish a life-like or human-like interaction based on the user's identified emotional state, effortlessly adjusting to the user's emotional state, and influencing it through the use of diverse emotions (Höök, 2014).

3.2.2. Intelligent User Interfaces

Intelligent user interfaces have been offered as a way to solve some of the issues that direct manipulation interfaces can't, such as information overflow, providing advice on how to utilize complex systems, and real-time cognitive overload. Intelligent user interfaces (IUIs) are also being advocated as a way to personalize or individualize computers, boosting their flexibility and appeal (Höök, 2000). Understanding what it means to be a computer user (which is more complicated than it seems) and how to produce associated goods and services that function together effortlessly is what human-computer interaction (HCI) is all about. It has evolved from early graphical user interfaces to include a wide range of interaction techniques and devices, multi-modal interactions, and model-based user interface specification tool support. The image below demonstrates the main fields that the HCI includes.

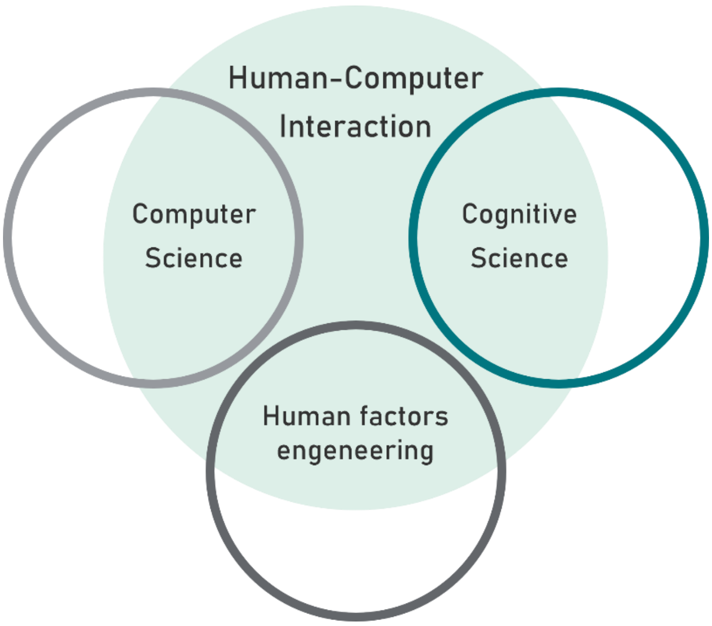

Figure 3 – The Multidisciplinary field of HCI. (Adapted from Höök, 2000).

IUIs are designed to integrate intelligent automated capabilities into this HCI (Zacharias et al., 2018) and to make information retrieval easier by recommending relevant information or by assisting system use, such as by providing explanations, completing tasks for the user, or customizing the interface (Hartmann, 2009).

IUIs attempt to answer the standard user interface question of how artificial intelligence can make the interaction between the user and the computer easier. In contrast to traditional HCI, IUIs focus on ways to include knowledge to aid the user in accomplishing activities, rather than just enabling the user to execute intelligent actions. In contrast to standard AI research, IUIs aim to improve the interface between the computer and humans rather than the computer itself (Hartmann, 2009).

Approaches like multimodal fusion and data-centric modeling have revealed the great potential of including users' emotive states to inform UIs. Affective computing, on the other hand, has yet to be implemented in ubiquitous computing contexts. How can one detect and describe the emotions that affective systems should incorporate in ubiquitous computing environments? This is a key question for this topic. As a result of this inquiry, we're trying to figure out if today's sensors can deliver the benefits of affective computing in our research domain (Tan et al., 2013). Aviezer et al. have brought attention to the importance of body postures in expressing and interpreting emotions. They demonstrated in their science paper that body posture can detect good and negative emotions just as well as face expression (Aviezer et al., 2012).

3.2.3. Chatbot's

Chatbots are computer programs with whom you can communicate, such as through messaging apps. There are two sorts of chatbots: one that works by following a set of rules, and another that employs machine learning. The capabilities of a chatbot that operates on rules are severely limited. It can only respond to commands that are highly specific. On the other hand, the second chatbot that uses machine learning has an artificial brain, also known as artificial intelligence. Not only does it understand commands, but it also understands language. (Jain & Jain, 2017). As it learns from the discussions it has with people, this bot continues to improve. Chatbots can make it simple for customers to acquire answers and information on their own time, using resources that they already have.

Speech is a complex communication that occurs on several levels, including "semantic, linguistic, articulatory, and auditory" (Campbell, 1997). Speech is regarded as the most natural mode of human communication, owing to the abundance of information that exists implicitly beyond the meaning of the spoken words. Converting voice to text via Automatic Speech Recognition (ASR) and mining speech information are two processes of speech information extraction; the resulting text can then be handled to recover the meaning of the words (Lee, 2004).

Chatbots can be utilized to handle client inquiries that come up repeatedly, allowing you to make better use of your existing resources to handle consumer intellectual queries. It can enable a successful collaboration between cognitive and AI technologies, resulting in improved outcomes, if they are implemented appropriately with better use cases. As a result, when integrating futuristic chatbot technology, it is vital to take a thorough and well-informed strategy. There has been a lot of progress overall. Chatbot platforms think that the power of chatbots will enhance the relationship between people who are addicted to chatting and are dedicated to making it as simple as possible for them to do so.

Specific health surveys, personal health-related reminders, communication with clinical teams, retrieving and analysing health data, and the translation of diagnostic patterns using behavioural indicators such as physical activity, sleep, and nutrition are all possible with chatbot technology (Abashev et al., 2017). Such technology has the potential to change the way healthcare is delivered, boosting uptake, fairness, and cost-effectiveness of services while closing the health and well-being gap (Harwich & Laycock, 2018).

From text to emojis to neuralink, the forms of language will evolve over time, but what will remain constant are our mental representations of the world and our need to communicate our thoughts (Felbo et al., 2017). Bots are the first step toward bridging the gap between humans and artificial general intelligence. The architecture and technologies we looked at can help you figure out what kind of bot to construct for your system, what to anticipate from it, and what tools to employ to make it (Nimavat et al., 2017).

3.2.4. Affective computing in Healthcare

In the medical field, artificial intelligence demonstrates a huge success in supporting and providing technological solutions to doctors and health professionals, and especially patients. With theoretical descriptions of human affective states as well as their influence on social, cognitive, physical, and other levels of human behaviour, Affective Computing aims to provide a full and credible research platform on which to ground research into the link between emotions and computers (Luneski et al., 2010). Furthermore, AC is interested in practical applications of computer technologies that have the potential to have a positive impact on people's everyday life by monitoring, communicating, or influencing their affective states. The relationship between emotions and human health, both mental and physical, is probably one of AC's most important research fields.

Researchers began discussing the potentials of Affective Computing in Medical Informatics shortly after Picard's book Affective Computing was published. Adaptive intelligent systems, which will increasingly rely on emotions to adjust for their own competing aims and limited resources, may benefit from this research of psychologists, neurologists, and psychiatrists on emotions (Webster, 1998). In 1999, Smith and Frawley presented their own perspective on how emotion research can be employed in medicine. They focused on two scenarios: the first, emotional user interfaces for health care professionals and patients in virtual worlds, and the second, emotions in computers as psychiatric support. Increasing physicians' empathy through interaction with a virtual patient, reacting emotionally to a virtual patient's response to physician-caused pain, such as touching a simulated burn victim, simulating a world in a disabled person to increase social involvement so they do not become depressed, and so on were among the potential applications listed in (Smith & Frawley, 1999).

Later, Picard created the term "affective medicine", citing research at the MIT Media Lab into emotionally aware and emotionally responsive computers, with a focus on certain types of emotions linked to health. The main goal was to teach computers to recognize some of the most common feelings humans have while engaging with technology today, such as annoyance, aggravation, and tension (Picard, 2001).

In 2004, it was the turn of Prendinger and Ishizuka, who took a more focused approach, defending the employment of tele-home healthcare technology such as AC and avatars. They demonstrated the state of the art in the process of measuring a user's physiological data in real time, interpreting it as emotions, and responding to the user's emotional states through life-like characters in the form of empathic feedback (Prendinger & Ishizuka, 2004).

Affective Computing and Medical Informatics (AmI) is one of the most important developing technologies that will be interconnected with AC in the future. AC, along with intelligent user interfaces, was identified by Alcaniz and Rey as topics that have the potential to affect the evolution of the ambient intelligence sector (Alcaniz & Rey, 2005). In an attempt to build synergies between the two domains, Cearreta et al. added AC as a component of AmI and reported considerable benefits (Cearreta et al., 2007). AmI technologies are used to improve users' daily activities by monitoring and identifying their emotional state and perhaps having a beneficial impact on their emotions by acting emotionally.

The increasing development and availability of invisible sensors and software tools that identify important emotional patterns, enabling consistent and objective monitoring of a user's internal emotional reaction, has led to the effective implementation of AmI and tele-home health care systems. The Affective Computing Group created new wearable sensors, including algorithms that accurately recognize human affective states and may be used by autistic people (Kaliouby et al., 2006). In 2015, sensors were already utilized for activity tracking by more than 1 in 4 people in the United States' daily smartphone-centric existence (Topol, 2015). Although sensor use is often short-lived, this sets an essential precedent for future acceptance. Smartphone electrocardiogram sensors that have been approved by the Food and Drug Administration are already accessible to consumers and provide rapid computer-assisted readings. Consumers will soon be able to do most routine laboratory tests using smartphone kits (Topol et al., 2015).

3.2.5. Challenges and Opportunities

As technology is constantly growing and expanding, several battles remain in their implementation. Induction techniques are one of the biggest issues in the practical application of Affective Sciences. "What is the most appropriate affect induction for a specific study domain?" for example. "And why?" you might wonder. "Is it even ethically acceptable?" you might wonder. "How can we guarantee that the produced affective states in the research setting are identical to affective states in the actual world?" is another topic. Situations that affect measurement or detection are comparable. Some people are reticent by nature and are not particularly communicative.

Another point to consider is the confidentiality and privacy of emotional data. Even if they are promised that the data would not be utilized for any other reasons, consumers in the Internet of Things era are likely to be concerned about data storage and later exploitation. The implementation of the detection results display is also a large design space. Furthermore, HF/HCI researchers may wish to develop a system to assist people in regulating their emotional states or mitigating the negative consequences of affective states on their work. Another important question in HF/HCI would be, "How can we improve performance by boosting emotional experience?".

As an opportunity, the constant growth and evolution of science and technologies presents a promising future in terms of solutions to be implemented in the health area. The number and variety of AC applications in the medical domain are determined by the rate of advancement of AC technologies and the development of synergies within the larger medical informatics/e-health research community. We should predict significant gains in demand for emotionally intelligent applications in the medical informatics sector as each of the sub-areas of AC (text, voice, face and gesture expression, physiology) advances (Luneski et al., 2010).

Surprisingly, AC pioneers have been focusing some of their research on medical applications of AC technology, such as study into emotions and autism or the development of wearable devices that can monitor emotions through physiological signals for health purposes.

4. STRATEGY FOR ENABLING THE CREATION OF GREATER EMPATHY BETWEEN HEALTH SUPPORT AI SYSTEMS AND USERS

4.1. ASSUMPTIONS

Using as a premise the literature review that was previously done on Patient Relationship Management, the appreciated aspects by the patient in his/her relationship with the doctor, Affective Computing and other technologies used in the medical environmental, it is possible to establish as assumptions that the service provided by health centers should consider meeting the following patient needs:

- Empathy;
- Transparency;
- Individuality;
- Trust;
- Responsiveness.

4.2. STRATEGY

As described in chapter 1.3., the goal of this dissertation will be to propose a strategy in affective computing that allows health services to improve their relationship with the patient/customer while walking the path of the technological age, in which many services are already integrated with their technological channels. This need arises from the gap found between what the patient feels when using this type of service and what is expected. The main goal is to identify how, through affective computing, it is possible to combat the emotional withdrawal felt by patients during their treatments.

In the table below are listed the factors pointed out by patients as the ones they value most during their contact with the hospital process (horizontal), and the applications of affective computing that were identified to match those requirements (vertical).

	Intelligent User Interface	**Chatbot's**	**Facial expression recognition**	**Speech adaptation**
Empathy	a)	b)	c)	d)
Transparency	a)	b)		
Individuality	a)		c)	d)
Trust		b)	c)	d)

Responsiveness	a)	b)		

Figure 4 – Patient Satisfaction factors / Affective Computing solutions.

Table 4 shows the relationship between the emotions that users have described and potential remedies in the field of affective computing. Green shading is seen at this crossing. The user satisfaction elements are displayed on the y-axis, and the affective computing solutions are displayed on the x-axis.

a) Intelligent User Interface

One important characteristic is that they actively support the user. Since this is non-intrusive, the agent will often assist by offering suggestions. In some circumstances, the user can direct the agent to take the suggested actions; this is exactly how programming by demonstration systems works. Some agent systems, like help systems, are only there to offer suggestions and counsel.

The interface as agent paradigm is one of the computer technologies that seek to support rather than replace its human users and can therefore contribute to the user feeling more empathy and individuality.

The upcoming generation of computer interfaces is expected to be heavily influenced by adaptive user interfaces. By adapting faster to the user, they are more responsive and are able to meet patient needs more quickly (Ross, 2000).

b) Chatbots

Chatbots are RPA software used for interactions with humans. They may be intelligent or not, but if they employ AI to analyze text or voice using NLP or voice recognition, they will comprehend user wants and provide solutions based on that understanding. While gathering preferences and purchasing habits, chatbots can assist staff in their work or facilitate effective customer service.

As previously written, chatbots can have two of the following characteristics: informative, in which case, the bots aim to provide the user with information that has been previously stored or is available from a fixed source. Usually, they rely on an information retrieval algorithm and retrieve the result of a query from the database or perform a string match. Here, the bot is highly responsive, empowering the user with the feeling that they are being provided with the information exactly as it is, in a transparent way; or conversation based, where these bots talk to the user as if they were another human. Their goal is to respond correctly to the sentence given to them. Therefore, they are often created with the aim of continuing the conversation with the user based on techniques such as cross-questioning, evasion, and deference, creating a bond of trust and transparency with the user. For example, Siri and Alexa.

c) Facial expression recognition (FER)

Face expressions are the delicate signals of the larger communication. Nonverbal communication is when people and animals communicate without using words, such as through gestures, facial expressions, body language, and paralanguage (Revina & Emmanuel, 2018). When it comes to identifying warning indications of serious illnesses by examining a patient's emotions and facial expressions, using AI in healthcare meets a difficulty. In the modern era, startups create affective computing-based AI helpers. The elderly and people with speech impairments who have trouble orally expressing their needs are catered to by these virtual assistants.

Face expressions are the delicate signals of the larger communication. Nonverbal communication is when people and animals communicate without using words, such as through gestures, facial expressions, body language, and paralanguage. A high-level framework that incorporates additional models can provide complementary information and further increase resilience, even though pure expression detection based on visible facial photos can produce encouraging results (Li & Deng, 2022).

With this solution, not only are we able to maintain the perception of the expressions and feelings that the user is feeling, as we would have in an interaction between two human beings, but we are also able to use the analysis of this component to adapt the speech throughout the interaction with the patient, in order to match the emotions that the patient is feeling.

d) Speech adaptation

Speech adaptation is one of the main components of affective computing, this technique enables the speech to be adjusted to whatever receiver is on the other side of the interface. Many publicly available toolboxes are capable of performing such acoustic feature computation. OpenSmile (Eyben, Wöllmer, & Schuller, 2010) is one such toolbox designed specifically for emotion recognition tasks; other generic audio/speech processing toolboxes—such as Praat (Boersma, 2001), Wavesurfer, and Voicebox—are all capable of extracting relevant acoustic features.

Using speech that is adjusted to what the user is feeling will make them feel more comfortable, more confident, and more satisfied with their communication with the interface. In addition, the user will feel that the speech is tailored to his situation, giving him a sense of uniqueness.

NLP-based chatbots are a guaranteed approach to boost patient engagement in the healthcare sector. This is so that healthcare chatbots built using natural language processing (NLP) can fully comprehend the intent of patient contact and create pertinent responses. Systems that just receive inputs and employ default answers stand in stark contrast to this.

Illustrated below is the flowchart process of the steps followed by a bot without Affective Computing technologies:

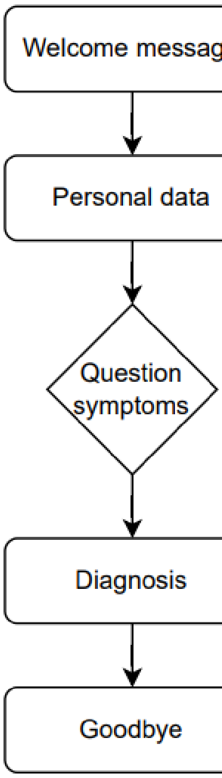

Figure 5 – Example of a bot process flowchart without AI.

The process can be divided into 5 steps, first the welcome, where the bot introduces and greets the user, and the user presents himself and communicates his personal data. After this first introduction, the bot asks about the symptoms that the patient feels and then the bot diagnoses the patient according to the symptoms presented to him. Finally, the last step of the process follows, the bot's goodbye.

Following is a similar example to the previous one, with the addition of the affective computation component in the bot:

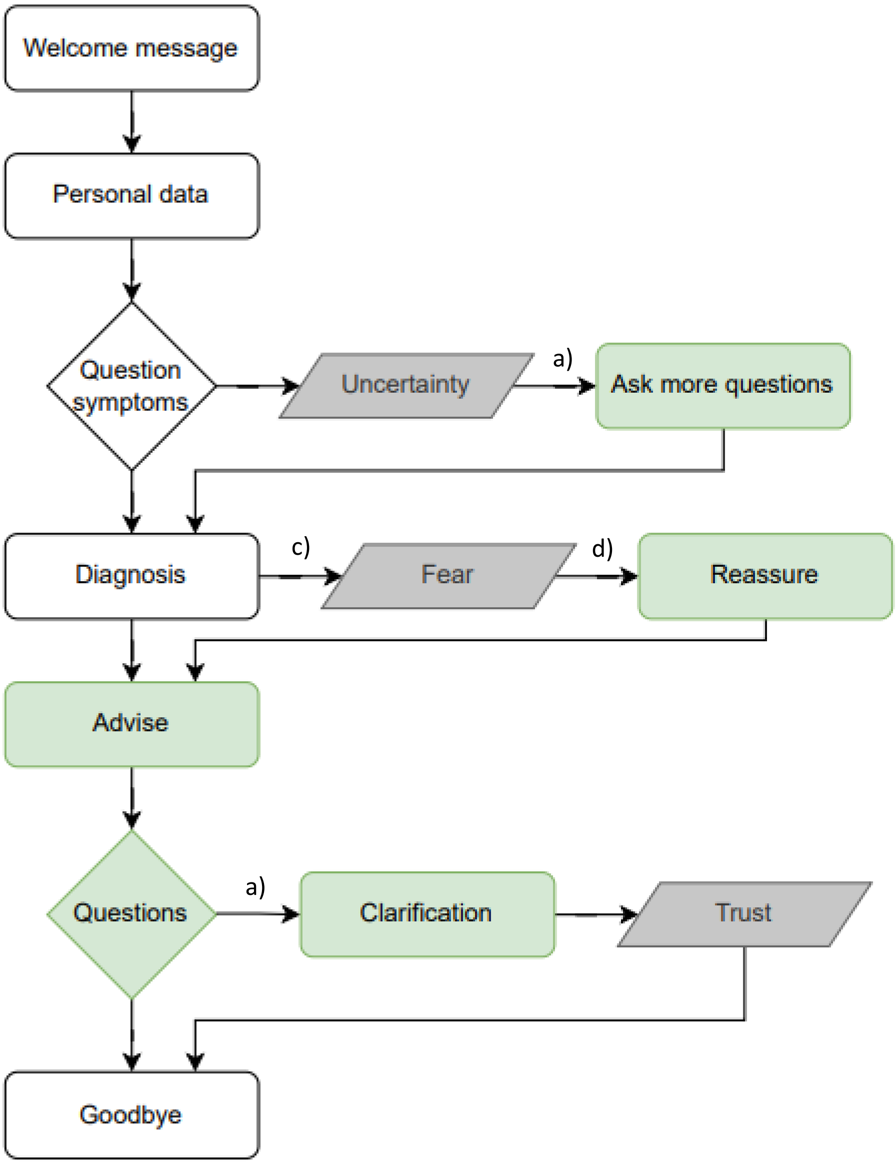

Figure 6 – Example of a bot process flowchart with Affective Computing features.

With the implementation of affective computing processes, another 5 steps, marked in green, are added in the interaction with the patient. These processes are based on the interpretation that the system considers according to the answers given by the patient.

The process starts in a similar way, beginning with a welcome and introduction to the bot. Then, it is the patient's turn to introduce himself and provide his personal information. Next, the bot asks about the symptoms that the patient feels and through the answers it analyses the feelings shown. In this case, if the patient is reticent or afraid, the bot asks more questions in order to better understand what the patient is feeling and through the affective computing component, perceives the user's state of mind, subsequently adapting its speech. Then, the bot communicates the diagnosis made and provides appropriate patient advice for treatment. Depending on the patient's posture, he/she may ask further questions or clarify any question that has been left unanswered.

After all doubts have been cleared up, and the patient demonstrates tranquility and confidence, the last step follows, the goodbye.

4.3. Use Case

To fulfil the goal of this thesis and in accordance with Peffers et al. (2007), a case study will be presented in which we can compare that which is the representation of a conversation between the bot and the patient (case 1), and how it would be with the implementation of affective computing (case 2).

- CASE 1

	Conversation
B	Good morning/good afternoon
B	Enter your name
P	Mariana Carreiro
B	Indicate your age
P	24
B	What is your problem?
P	Some lighter patches have appeared on my skin and I don't know what they could be
B	Does it itch?
P	No
B	It is probably pityriasis versicolor, but clinical observation and mycological examinations will be necessary to confirm the presence of the fungus.
B	Make an appointment with your dermatologist.

Figure 7 – Case 1: Normal bot.

- CASE 2

		Affective Computing features
B	Good morning/good afternoon	
B	Welcome! I hope you are well.	a) Intelligent User Interface.
B	I'm John, what's your name?	
P	Mariana Carreiro	
B	Thanks!	
B	How old are you, Mariana?	It uses the user's name to show individuality in the speech.
P	24	d) Speech adaptation.
B	What can I do for you?	c) Facial expression recognition. If it senses panic/uncertainty from the patient then reassure.
P	Some lighter patches have appeared on my skin and I don't know what they could be	
B	Does it itch?	
P	No	
B	It doesn't sound complicated, it is probably pityriasis versicolor. It is a superficial dermatological infection caused by a fungus called Malassezia furfur, which naturally lives on human skin.	d) Speech adaptation. Transparency.
B	To confirm this diagnosis, clinical observation and mycological examinations will be necessary to confirm the presence of the fungus.	
B	Make an appointment with your dermatologist.	
B	Need more information?	
P	No	
B	What else can I do for you?	
P	Nothing. Thanks	
B	Ok, thanks Mariana! Hope you get better.	a) Intelligent User Interface.

Figure 8 – Case 2: Bot with Affective Computing features.

In case 2, the bot uses affective computing strategies to create empathy with the user. It starts by introducing itself and showing friendliness in the speech, uses communication strategies, such as addressing the user by name, showing individuality in the discourse. The age of the patient also serves as a guideline for the type of language and words to be used later. With the answers given by the user and the facial recognition of expressions, the bot adapts its speech and suggests actions to be taken by the patient, always paying attention to the details demonstrated.

Just like a great agent, the goal of the interaction in case 2 is to turn every conversation into an opportunity to engage and delight, because it understands intent, responds like a human and reflects the speaker's intention to collaborate with the patient and provide the best possible interaction.

The latest advances in artificial intelligence and new school of thought have the power to fundamentally alter how customers interact with businesses, enabling them to deliver the best services in a way that appeals to contemporary clients. A medical bot gives a customized analysis based on symptoms, particularly in the field of medicine. With the inclusion of support for more medical parameters, such as symptom strength, duration, location, and a more thorough description of symptoms, the ability to diagnose and identify bot symptoms will be greatly improved in the future (Ayanouz et al., 2020).

With healthcare chatbots, even during a pandemic, patients are able to reach professionals at the moment of need. Using Conversational AI for the healthcare industry makes it easier for patients to access healthcare during emergencies, regardless of their location (Bansal, S. 2022). According to a survey conducted by SalesForce, 86% of patients believe in getting a response from a chatbot rather than filling out a website form.

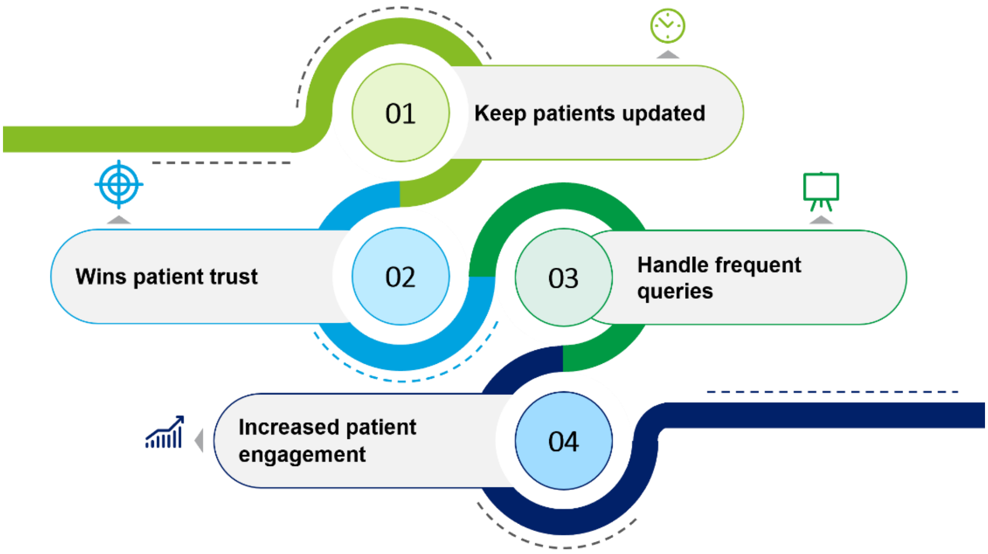

Figure 9 – 4 Key Benefits of Healthcare Chatbots.

Patients are never left unattended when using chatbots, especially with sentiment analysis features. They gain patients' trust by responding quickly and effectively. For instance, if one area of your hospital focuses solely on patient satisfaction and reporting, there is no waiting period and patients receive answers to their questions with minimal effort. Chatbots help your hospital in this way. Patients' pleasure is greatly enhanced by chatbots.

5. EVALUATION

This chapter will provide a detailed explanation of the scientific technique used for the thesis evaluation.

In order to evaluate the strategy, three in-depth qualitative interviews have been conducted. These artifacts were shown to three healthcare specialists who responded to three quality assessment questions while taking into account the sixth Hevner et al. (2004) guideline

5.1. INTERVIEWS PLANNING

Individual interviews were the strategy used in these evaluation sessions. Each expert was questioned separately, and consent to the session being recorded and transcribed.

The interviews were accomplished between 18th October and 2nd February, and the experts interviewed were:

- Dr. Tiago Harper Maia (THM): Intensive Care Doctor at Centro Hospitalar Universitário do Porto;
- Maria João Veiga (MJV): Nurse at Centro Clínico de Lisboa – Caixa Geral de Depósitos;
- Lorena Falcão Lima (LFL): Scientific Researcher at Escola Nacional de Saúde Pública – NOVA.

Each interview was followed by the artifacts' presentation (Annex 1) and included three questions:

1. Question 1 (Q1): Do you consider the proposed framework as useful and why? If not, why do you believe it is not?
2. Question 2 (Q2): Do you have any criticism towards the proposed framework? Please explain.
3. Question 3 (Q3): Do you have any recommendation or suggestions for further improvements of the proposed framework? Please justify.

All interviewees agreed to be recorded to enable transcription of the interview for further discussion and improvement of the artifact.

5.2. Interviews Description

The interviews conducted with the three health professionals are intended to analyze the usefulness, quality and contribution of the model proposed in this dissertation. It also provides an analysis of the limitations and potential challenges of the proposed model in the health industry.

Q1: Do you consider the proposed framework as useful and why? If not, why do you believe it is not?

All interviewees agreed that the proposed strategic model is both applicable and useful, considering some adjustments.

THM reminds that organizations and hospitals are at different levels of maturity regarding artificial intelligence but that, regardless of where the proposal is implemented, it would "always be quite positive for the service and the patient". He also adds the need to have " more projects that combine technology and health with a view to benefiting the patient experience and the quality of the service delivered".

MJV stresses the fact that it is very important to maintain a close relationship with the patient and that technological systems should be used and invested in, but that one should "not underestimate the contact with the patient and the attention to detail achieved by a human being". Hence, it reinforces the relevance of the problem identified and the importance of the topic of this dissertation for the health industry.

LHF considers the topic very "relevant and that it should be valued". She explains that affective computing is a technology that should be invested in, and that it should be understood which health sectors can start this work in a pilot way. She also emphasizes that the adoption of AI not only improves the patient experience, but also makes it possible to improve the efficiency of consultations and diagnoses. Through affective computing, it makes it possible to maintain "the healthy and trusting relationship that the patient and the doctor should have".

Q2: Do you have any criticism towards the proposed framework? Please explain.

Regarding the strategic model, THM finds it necessary to clarify the receptiveness that exists in Portugal for the implementation of these affective computing systems and the corresponding geographical alignment of the proposal made in order to specify the technical components necessary for its implementation. The user's needs in one place may be a more specific requirement due to various contexts or certain vulnerabilities that the patient is involved in their country, for example, in access issues. However, "if indicators related to the affective field are developed, they will be indicators that will exist regardless of the country where it is being implemented” and therefore possible to transpose and demonstrate a greater impact of the work.

MJV reinforces the contribution that would be to get practical feedback on the proposed strategic model in order to assess the impact it would have on patients and their relationship with health services, “only then will the true impact of the proposal be perceived”. She also pointed to the limited diversity of examples shown in the proposal of where these affective computing systems could be used, mentioning the possible integration in teleconsultation.

In LHF's opinion, a practical strategic plan would have been an excellent addition to the submitted proposal as it would "make it more sustainable and relatable". She suggested that partnerships with other colleges and organizations should be established to carry out a pilot project where the proposed approach could be put into practice and analyzed. This opinion can also be considered a time limitation of this research, considering that this model would be more extensive and would specify the implementation of the framework, which implies costs and longer time.

Q3: Do you have any recommendation or suggestions for further improvements of the proposed framework? Please justify.

Portugal may not be a big enough market if the goal is to "make money from the business", but it is ideal for "testing technologies" and "getting quick feedback and insights", in THM‘s opinion. For him, it is very important to start implementing this type of strategy in hospitals in Portugal, where the medical service is still far behind compared to other countries in Europe and the United States.

MJV suggests trying to understand which specialty or health services or which hospitals, "probably the private ones, will be more open" where implementing the proposed strategy will be more efficient. Maria reinforces the importance of patient wellbeing and how their view of the clinical process they are undertaking impacts on the final outcome.

As a follow-up to what she had mentioned earlier, LHF suggests carrying out a pilot project-study in line with other countries, where affective computing services are already being used in healthcare, so that data can be cross-checked, and critical analyses can be made with a significant audience. In his opinion, aligning this project with a clinical specialty where you can quickly evaluate its results, such as emergency sectors, will be the most effective way to analyze the viability of the model.

All interviewees mentioned in common that the "patient is the center of treatment" which once again demonstrates the importance of the study carried as well as the development of the strategic model presented which promotes the improvement of this experience for the patient.

Overall, all interviewees commended the investigation and resultant proposal. The presented strategic model was considered relevant. According to the interviewees, this investigation can materialize ideas through research and is essential to improve this academy and industry area of research, which reflects an excellent job.

The section will be followed up by section *5.3 Discussion*, where the commonalities and differences of all conducted interviews will be thoroughly synthesized and evaluated.

5.3. Discussion

Three separate analyses relating to usefulness, implementation viability, and improvements based on feedback and suggestions generated during the validation phase will be conducted in this part. The proposed framework will then be evaluated generally based on the preceding study.

All interviewees concurred that the suggested framework is extremely valuable when it comes to the recommended strategic model that was provided and its utility, as was already indicated.

Regarding the utility of the proposed framework, it was stated that the future of hospitals would depend on their ability to adopt cutting-edge technology that will bring machines and people closer together. Humans would be released from low-value work and given more specialized and human-centered tasks that machines cannot yet complete. All this, without underestimating the most important component of a relationship between patient and health services, which is trust. As the interviews were conducted with health specialists, all stressed the importance of implementing affective computing systems so that the relationship that has been built over the years is not lost.

Also, an interesting curiosity in the point of view of one interviewee, was how the new generation will adapt quickly to this new era of digitalization and how they will be drivers of non-contact with doctors. Further emphasizing the need to implement the proposed strategic model to preserve this relationship.

Concerning criticisms and observations on what was offered and its viability, all respondents agreed that it is a concept that serves its goal, filling a gap that exists in the services of regarding the automation of processes, which grows more remote from the persons involved as time passes.

It was unanimous among the interviewees that a more practical implementation strategy needed to be created and it was suggested that a pilot project be created to trigger the process of using affective computing in health in Portugal, with the collaboration of entities where artificial intelligence transformation processes had already started. The other recommendation made was the creation of

KPI's and measurement indicators that allow the comparison and monitoring of the results obtained from the implementations that were developed.

Both recommendations made have been considered highly valuable for the development of the strategy to be implemented and will be proposed as future research in the next chapter.

Despite the small sample size, the results of the interviews add to the already growing evidence that the use of Affective Computing, given a highly technological healthcare system, in this context would benefit the user, as they would feel more comfortable and more likely to air their concerns.

6. CONCLUSIONS

6.1. SYNTHESIS OF THE DEVELOPED WORK

The objective of this study was to propose a strategy in the area of affective computing to enable the creation of greater empathy between health support AI systems and users. Given that this is a theoretical study, the chosen method was design science research, a methodology that relies on four major premises: the search for flaws, the making of suggestions to correct the identified flaws, the validation of the suggestions made, and lastly the update of the initial proposals taking into account the feedback received during validation.

In the first phase, the main concepts inherent to the topic in hand were identified and studied, after which an investigation was conducted to determine which AI and Affective Computing technologies are currently being used in the healthcare section, and what are the determinants of the patient-health system relationship. For this purpose, it was also necessary to understand some of the emotions perceived by the users and some neurological factors associated with the perception of human satisfaction.

After comparing the users' needs with the technologies offered in the technological process of the health system, it became clear that there is a gap to be filled in an ecosystem that increasingly becomes more technological and with prospects of expansion so striking. The feelings of empathy, trust, and transparency that are so valuable from the patient's perspective have to be taken into account in this prospect of artificial intelligence technologies in healthcare interfaces.

By taking into account the identified factors, the currently available technologies and the potential uses for new ones, an artifact was proposed. In order to comprehend if the suggestions that were put forward made a real contribution to the resolution of the problem, a set of interviews was conducted with health professionals.

The first objective was accomplished through the study of emotions such as empathy, familiarity and satisfaction. The second objective was achieved by reviewing the literature on artificial intelligence and affective computing. The third objective was addressed by designing the proposal for the use of affective computing in technological systems in healthcare, in order to benefit the relationship between the patient and the industry platforms.

Furthermore, to achieve the final objective, which facilitates a more concrete answer to the research question, a use case was applied to demonstrate the contribution of the adoption of affective computing in healthcare platforms in developing the relationship with the patient and their satisfaction. Lastly, and in order to fulfil the last objective of this dissertation, a set of interviews were carried out with professionals in the health area, where their expertise was essential to corroborate the defined strategy, as well as, through their knowledge, to improve this same proposal.

6.2. LIMITATIONS

As this is an academic research report, some limitations were encountered and aspects that could be improved were identified. The major limitations concerning this study are mainly due to time and scope, the sample used for the interviews, as this research was conducted to complete a master's thesis and was guided by its deadline.

One of the main limitations was the impossibility of implementing the proposed strategy in practice, thus being a strategic model only theoretical and restricting its robustness. Regarding the initial requirements, the construction of a bot with the concepts of the artefact was not possible to implement. Due to the short time available it was not possible to build a real example chabot to better illustrate the idealised proposal. This limitation also conditions the evaluation "on the ground" of the proposal presented, limiting it to a theoretical model of the research developed.

Other limitation of the proposed solution was the rare use of affective computing techniques in health in Portugal. This factor made it impossible to demonstrate in real time the benefits and results that this solution brings to the industry.

6.3. FUTURE WORK

In order to add more substance to the proposed strategic model, it would be important, following the experts' suggestion, to take a practical approach to the model. This pilot project, as mentioned above, should be accompanied by result indicators and KPI's that allow the comparison and qualitative and quantitative analysis of the results obtained.

The implementation of the proposed model in a hospital specialty would be the most efficient way to analyze the sustainability of the proposal presented. The question is, in which of the medical specialties will the implementation of this strategic model be most useful? The ideal would be to find the specialty that will be able to aggregate the component of speed of implementation and results with the reduction of operational cost. In this way, it will be possible to arrive more efficiently at clear results of benefit versus implementation costs.

Other needs identified in this research are "Which type of health service, will be more willing to test the implementation of this strategy? A partnership with other organizations where artificial intelligence and namely affective computing is already used would have an even greater contribution to the comparison of results.

Beyond the affective relationship with the patient, all the analytical and computational benefits of implementing affective computing and AI systems could also be the subject of future research.

BIBLIOGRAPHY

Abashev, A., Grigoryev, R., & Grigorian, K. (2017). Programming tools for messenger-based chatbot system organization: Implication for outpatient and translational medicines. *BioNanoScience*, 7(2), 403–407.

Alcaniz, M., & Rey, B. (2005). New technologies for AmI. *AmI: The Evolution of Technology, Communication and Cognition towards the Future of HCI*, 3-16.

Aviezer, H., Trope, Y., & Todorov, A. (2012). Body cues, not facial expressions, discriminate between intense positive and negative emotions. *Science 338*, 1225–1229.

Ayanouz, S., Abdelhakim B., & Benhmed, M. (2020). A Smart Chatbot Architecture based NLP and Machine Learning for Health Care Assistance. *Association for Computing Machinery.* https://doi.org/10.1145/3386723.3387897

Baashar, Y., Mahomood, A., Almomani, M., & Alkawsi, G. (2016). Customer relationship management (CRM) in healthcare organization: A review of ten years of research. *3rd International Conference on Computer and Information Sciences*, 97-102.

Baashar, Y., Alhussian, H., Patel, A., Alkawsi, G., Alzahrani, A., Alfarraj, O., & Hayder, G. (2020). Customer relationship management systems (CRMS) in the healthcare environment: A systematic literature review. *Computer Standards and Interfaces,* 71. https://doi.org/10.1016/j.csi.2020.103442

Bansal, S. (2022). Healthcare Chatbot – Key Advantages & Use Cases. *Ameyo*. https://www.ameyo.com/blog/key-advantages-and-use-cases-of-healthcare-chatbot/

Basch, M. F. (1983). Empathic understanding: A review of the concept and some theoretical considerations. *Journal of the American Psychoanalytic Association*, 31, 101–126.

Basu, K., Sinha, R., Ong, A., & Basu, T. (2020). Artificial Intelligence: How is It Changing Medical Sciences and Its Future?. *Indian journal of dermatology, 65(5),* 365–370. https://doi.org/10.4103/ijd.IJD_421_20

BearingPoint & ESSEC. (2012). Hospitals: from curing to caring - Influencing the behaviours of patients can greatly improve the quality of healthcare delivery according to our survey and case studies. *BearingPoint Institute.*

Bertakis, K., Roter, D., & Putnam, S. (1991). The relationship of physician medical interview style to patient satisfaction. J Fam Pract, 175-81.

Benz, G. & Paddison, N. (2004). Developing patient-based marketing strategies. Healthcare executive, vol. 19, 40-42.

Bjertnaes, O., Sjetne, I., & Iversen, H. (2011). Overall patient satisfaction with hospitals: Effects of patient-reported experiences and fulfilment of expectations. *BMJ Qual. Saf.,* 21, 39–46.

Bucher, T., & Winter, R. (2008). Dissemination and importance of the ''Method'' Artifact in the context of design research for information systems. *Proceedings of the Third International Conference on Design Science Research in Information Systems and Technology,* 39–59.

Campbell, J. (1997). Speaker recognition: a tutorial. *Proceedings of the IEEE*, 85(9), 1437-1462.

Campbell, R., & Babrow, A. (2004). The Role of Empathy in Responses to Persuasive Risk Communication: Overcoming Resistance to HIV Prevention Messages. *Health Communication* 16, 159–182.

Cath C. (2018). Governing artificial intelligence: ethical, legal and technical opportunities and challenges*. Phil. Trans. R. Soc. A*. http://dx.doi.org/10.1098/rsta.2018.0080

Cearreta, I., Lopez, J., Hernandez, C., Garay, N., Grana, M., & Alvarez, A. (2007). Affective computing as a component of AmI. *Proceedings of the 10th Joint Conference on Information Sciences*, 1580-1586.

Chen, R., & Hsiao, J. (2012). An investigation on physicians' acceptance of hospital information systems: a case study. *Int. J. Med. Inf.,* 810-820.

Choudhury, A. (2020). AI in healthcare: Improving human interface for patient safety. *ISE Magazine.* https://www.iise.org/iemagazine/2020-02/html/choudhury/choudhury.html

Daily, S., James, M., Cherry, D., Porter, J., Darnell, S., Isaac, J., & Roy, T. (2017). Affective Computing: Historical Foundations, Current Applications, and Future Trends. *Emotions and Affect in Human Factors and Human-Computer Interaction*, 213-231. https://doi.org/10.1016/B978-0-12-801851-4.00009-4

Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. Future healthcare journal, 6(2), 94–98. https://doi.org/10.7861/futurehosp.6-2-94

Davis, M. (1983). Measuring individual differences in empathy: Evidence for a multidimensional approach. *Journal of Personality and Social Psychology*, 44(1), 113-126. doi:10.1037/0022-3514.44.1.113

Davis, M., Hull, J., Young, R., & Warren, G. (1987). Emotional reactions to dramatic film stimuli: The influence of cognitive and emotional empathy. *Journal of Personality and Social Psychology*, 52(1), 126-133. doi:10.1037/0022-3514.52.1.126

Derksen, F., Bensing, J., Kuiper, S., Meerendonk, M., & Lagro-Janssen, A. (2015). Empathy: what does it mean for GPs? A qualitative study. *Family Practice*, 94–100. Volume 32, Issue 1. https://doi.org/10.1093/fampra/cmu080

Dilmegani, C. (2021). Affective Computing: In-Depth Guide to Emotion AI. *AIMultiple*. https://research.aimultiple.com/affective-computing/

Eisenberg, N., & Miller, P. (1987). The relation of empathy to prosocial and related behaviors. *Psychological Bulletin*, 101(1), 91–119. https://doi.org/10.1037/0033-2909.101.1.91

Felbo, B., Mislove, A., Søgaard, A., Rahwan, I., & Lehmann, S. (2017). Using millions of emoji occurrences to learn any-domain representations for detecting sentiment, emotion and sarcasm. *Association for Computational Linguistics*, 1615-1625. doi: 10.18653/v1/D17-1169

Fraser, H., Coiera, E., & Wong, D. (2018). Safety of patient facing digital symptom checkers. *The Lancet 392, 10161,* 2263–2264.

Gavurova, B., Kovac, V., & Khouri, S. (2020). Purpose of patient satisfaction for efficient management of healthcare provision. *Pol. J. Manag. Stud.,* 22, 134–146.

Gavurova, B., Dvorsky, J., & Popesko, B. (2021). Patient Satisfaction Determinants of Inpatient Healthcare. *International Journal of Environmental Research and Public Health*, 18. https://doi.org/10.3390/ijerph182111337

Greenhalgh, T., Wood, G., Bratan, T., Stramer, K., & Hinder, S. (2008). Patients' attitudes to the summary care record and HealthSpace: qualitative study. *BMJ*. doi:10.1136/bmj.a114

Goel, M., Brown, T., Williams, A., Cooper, A., Hasnain-Wynia, R., & Baker, D. (2011). Patient reported barriers to enrolling in a patient portal. *Journal of the American Medical Informatics Association*, 18 Suppl 1. i8-12. 10.1136/amiajnl-2011-000473

Halpern, J. (2003). What is Clinical Empathy?. *Blackwell Science,* 670-674. Volume 18.

Hartmann, M. (2009). Challenges in Developing User-Adaptive Intelligent User Interfaces. *Proceedings of the 17th Workshop on Adaptivity and User Modeling in Interactive Systems at Lernen Wissen Adaptivit* (LWA).

Harwich, E. & Laycock, K. (2018). Thinking on its Own— AI in the NHS. *Reform*. https://reform.uk/research/think ing-its-own-ai-nhs

Haux, R., Winter, A., Ammenwerth, E., & Brigl, B. (2003). Strategic Information Management in Hospitals: An Introduction to Hospital Information Systems. *Springer*.

Hevner, A. R., March, S. T., & Park, J. (2004). Design Research in Information Systems Research*. MIS Quarterly, 28(1),* 75-105.

Hojat, M. (2007). Empathy in patient care: Antecedents, development, measurement, and outcomes. *Springer Science and Business Media*.

Höök, K. (2000). Steps to take before intelligent user interfaces become real. *Interacting with Computers 12*, 409–426. https://doi.org/10.1016/S0953- 5438(99)00006

Höök, K. (2014). The Encyclopedia of Human-Computer Interaction, 2nd Ed. Chapter 12.

Hung, S., Hung, W., Tsai, C., & Jiang, S. (2009). Critical factors of hospital adoption on CRM system: Organizational and information system perspectives. *Decision Support Systems* 48, 592–603.

IANS. (2017). Indian scientists tap AI to identify aggressive breast cancer. *Indian Express.*

Jain, N., & Jain, A. (2017). A Survey on Popularity of Chat-Bots. *International Conference On Emanations in Modern Technology and Engineering*, 277–280. Volume 5. Issue: 3.

Jennings, B., Heiner, S., Loan, L., Hemman, E., & Swanson, K. (2005). What really matters to healthcare consumers. *J Nurs Adm*, 35(4). doi: 10.1097/00005110-200504000-00006

Jutzi, T., Krieghoff-Henning, E., Holland-Letz, T., Utikal, J., Hauschild, A., Schadendorf, D., Sondermann, W., Fröhling, S., Hekler, A., Schmitt, M., Maron, R., & Brinker, T. (2020). Artificial Intelligence in Skin Cancer Diagnostics: The Patients' Perspective. *Front. Med*. doi: 10.3389/fmed.2020.00233

Kairy, D., Tousignant, M., Leclerc, N., Côté, A., & Levasseur, M. (2013). The Patient's Perspective of in-Home Telerehabilitation Physiotherapy Services Following Total Knee Arthroplasty. *International Journal of Environmental Research and Public Health, 10,* 3998-4011.

Kaliouby, R., Picard, R., & Barron-Cohen, S. (2006). Affective computing and autism. *Annals of the New York Academy of Sciences*, 228–248.

Kaplan, A., Haenlein, M. (2018). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62(1),* 15-25.

Kestenbaum, R., Farber, E., & Sroufe, L. (1989). Individual differences in empathy among preschoolers: Relation to attachment history. *N. Eisenberg (Ed.)*, 51–64.

Khoshraftar, A., Yazdi, M., Ibrahim, O., Amini, M., Nilashi, M., Khoshraftar, A., & Talebi, A. (2011). Improving the CRM System in Healthcare Organization. *International Journal of Computer Engineering & Science*, 28-35. Volume 1, Issue 2.

Kim, S., Kaplowitz, S., & Johnston, M. (2004). The effects of physician empathy on patient satisfaction and compliance. *Evaluation & the Health Professions*, 27(3), 237–251.

Kruse, C. S., Krowski, N., Rodriguez, B., Tran, L., Vela, J., & Brooks, M. (2017). Telehealth and patient satisfaction: a systematic review and narrative analysis. *BMJ Open.* https://bmjopen.bmj.com/content/7/8/e016242

Kumar, P.,T.V, N., & N.A, V. (2017). Health Monitoring and Logging System for Patients using Wireless Standalone Network. *International Journal of Advanced Research in Computer Science and Software Engineering*. 7. 806-814. 10.23956/ijarcsse/V7I5/0190.

Lau, A., & Staccini, P. (2019). Artificial Intelligence in Health: New Opportunities, Challenges, and Practical Implications*. Yearb Med Inform,* 174-178. DOI: 10.1055/s-0039-1677935

Lee, C. (2004). From knowledge-ignorant to knowledge-rich modeling: a new speech research paradigm for next generation automatic speech recognition.

Li, S., & Deng, W. (2022). Deep Facial Expression Recognition: A Survey. *IEEE – Transactions on Affective Computing.*

Lisetti, C., & Lerouge, C. (2004). Affective Computing in Tele-home Health. *IEEE – Advancing Technology for Humanity.*

Lisetti, C. & Schiano, D. (2000). Automatic facial expression interpretation. *Pragmatics and Cognition, John Benjamins Publishing Co., 8,* 185-235.

Loureiro, J., Pereira, M., Trancas, B., Caldas-De-Almeida, J., & Castro-Caldas, A. (2011). Empatia na relação médico-doente, *Acta Med Port*, 431-442.

Luneski, A., Konstantinidis, E., & Bamidis, P. D. (2010) Affective Medicine: a review of Affective Computing efforts in Medical Informatics. *Methods of Information in Medicine, 49(3)*. 207-218. https://pubmed.ncbi.nlm.nih.gov/20411209

March, S. T., & Smith, G. F. (1995). Design and natural science research on information technology. *Decision Support Systems, 15(4)*, 251–266.

McKeon, J. (2021). What Data Privacy Risks Are Associated with Mobile Health Apps? *HealthITSecurity*.

Mehra, P., & Mishra, A. (2021). Role of Communication, Influence, and Satisfaction in Patient Recommendations of a Physician. *Vikalpa: The Journal for Decision Makers*, 46(2), 99–111. https://doi.org/10.1177/02560909211027090

Meskò, B., Drobni, Z., Bényei, E., Gergely, B., & Gyorffy, Z. (2017). Digital health is a cultural transformation of traditional healthcare. *Mhealth,* 3-38.

Miller, D., & Brown, E. (2018). Artificial Intelligence in Medical Practice: The Question to the Answer?, *The American Journal of Medicine*, 129-133. Volume 131, Issue 2. https://doi.org/10.1016/j.amjmed.2017.10.035

Monem, H., Hussin, A.R., Sharifian, R., & Shaterzadeh, H. (2011). CRM software implementation factors in hospital: Software & patient perspectives. *Malaysian Conference in Software Engineering,* 159-164.

Nadarzynski, T., Miles, O., Cowie, A., & Ridge, D. (2019). Acceptability of artificial intelligence (AI)-led chatbot services in healthcare: A mixed-methods study. *Digital Health, 5,* 1-12.

Nimavat, K. & Champaneria, T. (2017). Chatbots: An Overview Types, Architecture, Tools and Future Possibilities. *International Journal of Scientific Research and Development*, 1019-1024. Volume 5, Issue 7.

Oinas-Kukkonen H., Räisänen T., & Hummastenniemi N. (2008). Patient relationship management: an overview and study of a follow-up system. *J Healthc Inf Manag,* 24-9. PMID: 19267028.

Pedersen, R. (2009). Empirical research on empathy in medicine - A critical review. *Patient Education and Counseling*, 307-322. Volume 76, Issue 3. https://doi.org/10.1016/j.pec.2009.06.012

Peffers, Ken., Tuunanen, T., Gengler, C., Rossi, M., Hui, W., Virtanen, V., & Bragge, J. (2006). The design science research process: A model for producing and presenting information systems research. *Proceedings of First International Conference on Design Science Research in Information Systems and Technology DESRIST*.

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2008). A design science research methodology for information systems research. *Journal of Management Information Systems*. https://doi.org/10.2753/MIS0742-1222240302

Picard, R. (1995). *Affective Computing*. The MIT Press.

Picard, R. (2001). Affective medicine: Technology with emotional intelligence. *Future of Health Technology*, 69-85

Poku, M., Behkami, N., & Bates, D. (2016). Patient Relationship Management: What the U.S. Healthcare System Can Learn from Other Industries. *Society of General Internal Medicine*. doi: 10.1007/s11606-016-3836-6.

Prendinger, H., & Ishizuka, M. (2004). What Affective Computing and Life-Like Character Technology Can Do for Tele-Home Health Care. *Workshop on HCI and Homecare: Connecting Families and Clinicians*.

Pyper, C., Amery, J., Watson, M., & Crook, C. (2004). Access to electronic health records in primary care-a survey of patients' views. *British Journal of General Practice*, 54, 38-43.

Ramesh, A., Kambhampati, C., Monson, J., & Drew, P. (2004). Artificial intelligence in medicine. *Annals of the Royal College of Surgeons of England*, *86(5),* 334-338.

Ratka, A. (2018). Empathy and the Development of Affective Skills. *American Journal of Pharmaceutical Education*, 82 (10) 7192. DOI: 10.5688/ajpe7192

Reddy, B., & Acharyulu, G. (2002). Customer relationship management (CRM) in health care sector - a case study on master health check. *Journal of the Academy of Hospital Administration*, 14.

Revina, M., & Emmanuel, S. (2018). A Survey on Human Face Expression Recognition Techniques. *Journal of King Saud University – Computer and Information Sciences.*

Ricciardi, W., Pita Barros, P., Bourek, A., Brouwer, W., Kelsey, T., Lehtonen, L., Anastasy, C., Barry, M., De Maeseneer, J., Kringos, D., McKee, M., Murauskiene, L., Nuti, S., Siciliani, L., & Wild, C. (2019). How to govern the digital transformation of health services. *European Journal of Public Health*, 7-12.

Roter, D., & Hall, J. A. (2006). Doctors talking with patients/ patients talking with doctors: Improving communication in medical visits. *Greenwood Publishing Group.*

Rowe, C. (2015). Healthcare CRM: Redefining Models and Optimizing Relationships. *HIMSS*.

Samoili, S., Cobo, M. L., Gómez, E., De Prato, G., Martínez-Plumed, F., & Delipetrev, B. (2020). AI Watch.Defining Artificial Intelligence. EUR 30117 EN. *Publications Office of the European Union.*

Sanders, J., Dubey, M., Hall, J., Catzen, H., Blanch-Hartigan, D., & Schwartz, R. (2021). What is empathy? Oncology patient perspectives on empathic clinician behaviors. *American Cancer Society*, 4258-4265. doi: 10.1002/cncr.33834

Santus, P., Picciolo, S., Proietto, A., Falcone, F., Mangiacavallo, A., Pellegrino, G., Sereno, F., Radovanovic, D., Blasi, F., Girbino, G., & Centanni, S. (2012). Doctor–patient relationship: A resource to improve respiratory diseases management. *European Journal of Internal Medicine, 442-446*. Volume 23, Issue 5. https://doi.org/10.1016/j.ejim.2012.04.004

Sharma, N. (2015). Patient centric approach for clinical trials: Current trend and new opportunities. *Perspectives in Clinical Research.* Vol 6. Issue 3.

Siau, K. (2003). Health care informatics. *IEEE Engineering in Medicine and Biology Society*, vol. 7, 1-7.

Singer, T., & Klimecki, O. (2014). Empathy and compassion. *Current Biology*, 875-878. Volume 24, Issue 18. https://doi.org/10.1016/j.cub.2014.06.054

Smajdor, A., Stöckl, A., & Salter, C. (2011). The limits of empathy: Problems in medical education and practice. *Journal of Medical Ethics*, 37(6), 380–383.

Smith, R., Frawley, W. (1999). Affective Computing: Medical Applications. *Proceedings of HCI International*, 843-847.

Sunarti, S., Fadzlul, R. F., Naufal, M., Risky, M., Febriyanto, K., & Masnina, R. (2020). *Gaceta Sanitaria*, S67-S70.

Tan, C., Schöning, J., Luyten, K., & Coninx, K. (2013). Informing Intelligent User Interfaces by Inferring Affective States from Body Postures in Ubiquitous Computing Environments. *In Proceedings of the 2013 International Conference on Intelligent User Interfaces.* https://doi.org/10.1145/2449396.2449427

Topol, E. (2015). The Patient Will See You Now: The Future of Medicine Is in Your Hands. *New York, NY: Basic Books.*

Topol, E. J., Steinhubl, S. R., & Torkamani, A. (2015). Digital medical tools and sensors. *JAMA, 313(4),* 353–354. https://doi.org/10.1001/jama.2014.17125

Tran, V., Riveros, C., & Ravaud, P. (2019). Patients' views of wearable devices and AI in healthcare: findings from the ComPaRe e-cohort. *Digital Medicine, 2(1).* https://doi.org/10.1038/s41746-019-0132-y

Vardasca, T.R., Martins, H.M., & Fonseca, D.F. (2011). Patient Relationship Management in public healthcare settings System architecture. *IEEE Communications Society*.

vom Brocke, J., Hevner, A., & Maedche, A. (2020) Introduction to Design Science Research. *Design Science Research.* https://doi.org/10.1007/978-3-030-46781-4_1

Webster C. (1998). Medical affective computing: medical informatics meets affective computing. *Stud Health Technol Inform*, 52.

Weng H., Steed J., Yu S., Liu Y., Hsu C., & Yu T. (2011). The effect of surgeon empathy and emotional intelligence on patient satisfaction. *Adv Heal Sci Educ,* 591–600. https://doi.org/10.1007/s10459-011-9278-3

Zacharias, J., Barz, M., & Sonntag, D. (2018). A Survey on Deep Learning Toolkits and Libraries for Intelligent User Interfaces. *ArXiv,* abs/1803.04818.

Annex

Interviews Presentation