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DIOGO ALBINO DE QUEIROZ

SMART MONITORING TOOL:
Intelligent Model for Monitoring Colorectal Cancer Patients in the Active Phase of Treatment

São Leopoldo, 2023

Diogo Albino de Queiroz

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Intelligent Model for Monitoring Colorectal Cancer Patients in the Active Phase of Treatment

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Advisor:
Prof. Dr. Cristiano André da Costa

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My wife, Eveline Queiroz,

To my dear wife for her patience, dedication, affection, love, friendship, and all support.

My children, Júlia Queiroz and Matheus Queiroz,

A blessing in my life. A blessing from God that gives me more strength to face challenges.

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RESUMO

O câncer colorretal é um dos mais prevalentes em homens e mulheres, e seu desenvolvimento está associado a diversos fatores de risco, como sedentarismo e hábitos alimentares. Além disso, ele impacta diretamente a qualidade de vida do indivíduo e sua rotina diária (trabalho, estudo, lazer, dentre outros), especialmente quando diagnosticado em estágio avançado. Atualmente, durante o período entre as sessões de quimioterapia não existe um monitoramento focado se o paciente está seguindo o tratamento, conforme orientado pela equipe médica, o que contribui para um baixo engajamento em ações para melhorar a sua condição clínica e autogerenciar os efeitos adversos do tratamento. Esse trabalho desenvolveu um modelo computacional, baseado em Inteligência Artificial e Internet das Coisas, para monitoramento dos pacientes com câncer em fase de tratamento ativo com o intuito de garantir maior engajamento do paciente ao tratamento por meio de interações e feedbacks individualizados e automatizados entre o paciente e o assistente virtual e/ou equipe multidisciplinar responsável pelo seu tratamento. Os dados foram armazenados em uma base de dados, e o time multidisciplinar era notificado quando a condição clínica do paciente indicava deterioração. O modelo funcionou de forma passiva e ativa, e o estudo foi realizado em três fases. A primeira fase foi realizada em dezembro de 2021, onde a equipe do Centro do Câncer de Sinop avaliou uma das ferramentas do modelo computacional. Na segunda fase o modelo foi aplicado em pacientes com câncer colorretal em fase de tratamento ativo no período de julho a dezembro de 2022. Todos os pacientes que atendiam os critérios de inclusão foram convidados a participar. Durante 8 semanas, os pacientes foram estimulados a relatarem os sintomas e efeitos adversos relativos ao tratamento, prática de atividade física e dados sobre sua alimentação. A avaliação dos resultados baseou-se na comparação entre os grupos de intervenção e controle. Os pacientes avaliaram o modelo por meio dos questionários de Experiência do Usuário (UEQ) e Usabilidade do Sistema (SUS). Na terceira fase foi avaliado a aplicação de um sistema recomendador integrado ao modelo proposto. Os resultados da primeira fase mostraram que o modelo foi eficaz na abordagem da usabilidade e experiência do usuário. As escalas de atratividade e eficiência do UEQ foram avaliadas como excelentes e as demais como boas. A usabilidade avaliada pelo SUS obteve média de 75 ± 7,14 e mediana de 72,5 (70-77,5). Na segunda fase, os pacientes que participaram do modelo relataram sinais e sintomas com maior precisão (controle: 64,7%; intervenção: 92,3%; p=0,1038). No grupo intervenção, a prática de atividade física foi mais eficaz, e a maioria dos pacientes (61,5%) interagiu com o chatbot por pelo menos 62,5% do período. Também se observou redução

estatística no consumo de bebidas alcoólicas e *fast food*, e aumento estatístico no consumo de frutas no grupo de intervenção. Por fim, na terceira fase os resultados sugerem que o sistema recomendador pode endereçar positivamente as expectativas do usuário. Desta forma, os resultados indicam que o modelo contribuiu para uma coleta de dados mais assertiva e maior engajamento do paciente no autogerenciamento dos sintomas e efeitos adversos do tratamento e do câncer. Além disso, o modelo contribuiu para aumentar a prática de atividades físicas leves pelos pacientes. As pontuações UEQ e SUS indicam que o modelo atendeu às expectativas dos usuários e teve usabilidade aceitável.

Palavras-chave: Estudo clínico; Câncer Colorretal; Internet das Coisas; *Chatbot*; Sistemas Especialistas; Sistemas Distribuídos.

ABSTRACT

Colorectal cancer is one of the most prevalent in men and women, and its development is associated with several risk factors, such as a sedentary lifestyle and eating habits. In addition, it directly impacts the individual's quality of life and daily routine (work, study, leisure, among others), especially when diagnosed in advanced stages. Currently, during the period between chemotherapy sessions, there is no follow-up to verify if the patient is following the treatment, as instructed by the medical team, which contributes to low engagement in actions to improve their clinical condition and self-manage the adverse effects of the treatment. This work aimed to develop a computational model, based on Artificial Intelligence and the Internet of Things, for monitoring cancer patients undergoing active treatment to ensure greater patient engagement in treatment through individualized and automated interactions and feedback between the patient and the virtual assistant and/or multidisciplinary team responsible for your treatment. Data were stored in a database, and the multidisciplinary team was notified when the patient's clinical condition indicated deterioration. The model worked both passively and actively, and the study was carried out in three phases. The first phase was carried out in December 2021, when the Sinop Cancer Center team evaluated one of the computational model tools. In the second phase, the model was applied to colorectal cancer patients undergoing active treatment from July to December 2022. All patients who addressed the inclusion criteria were invited to participate. For 8 weeks, patients were encouraged to self-report symptoms and adverse effects related to treatment, physical activity, and data about their diet. The outcome assessment was based on the comparison between the intervention and control groups. The patients evaluated the model through the User Experience Questionnaire (UEQ) and System Usability Scale (SUS) surveys. In the third phase, the application of a recommendation system integrated to the proposed model was evaluated. The results of the first phase showed that the model was effective in addressing usability and user experience. We evaluated the UEQ attractiveness and efficiency scales as excellent and the others as good. The usability evaluated by the SUS obtained a mean of 75 ± 7.14 and a median of 72.5 (70-77.5). In the second phase, patients who participated in the model reported signs and symptoms more accurately (control: 64.7%; intervention: 92.3%; p=0.1038). In the intervention group, the practice of physical activity was more effective, and most patients (61.5%) interacted with the chatbot for at least 62.5% of the period. There was also a statistical reduction in the consumption of alcoholic beverages and fast food, and a statistical increase in fruit consumption in the intervention group. Finally, in the third phase, the results suggest that the recommender system can positively

address user expectations. Therefore, results indicate that the model contributed to more assertive data collection and greater patient engagement in self-management of symptoms and adverse effects of treatment and cancer. Moreover, the model contributed to increasing the practice of light physical activity. UEQ and SUS scores indicate that the model met users' expectations and had acceptable usability.

Keywords: Clinical Study; Colorectal Cancer; Internet of Things; Chatbot; Expert Systems; Distributed Systems.

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NOMENCLATURE

AI	Artificial Intelligence
CRC	Colorectal Cancer
Cecans	Sinop Cancer Center
EORTC	European Organization for Research and Treatment of Cancer
ICF	Informed Consent Form
IoT	Internet of Things
PICOS	Participants, Interventions, Comparisons, Outcomes, Study Design
PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analyses
RCT	Randomized Controlled Trial
RoBANS	Risk of Bias Assessment Tool for Non-randomized Studies
SD	Standard Deviation
SMT	Smart Monitoring Tool
SUS	System Usability Scale
UEQ	User Experience Questionnaire

CONTENTS

1 INTRODUCTION

The National Cancer Institute (INCA) defines cancer as a disordered growth of abnormal cells that can invade organs and tissues and migrate to other body regions through a process known as metastasis. Cancer is the second leading cause of death globally, accounting for approximately 9.6 million deaths, corresponding to one-sixth of fatalities in 2018 (WHO, 2020). Colorectal cancer (CRC) is the third type of cancer with the highest incidence in men and the second most common in women worldwide, accounting for more than 10% of all patients diagnosed with cancer (IARC, 2019). It is a cancer with high incidence, prevalence, and mortality (INCA, 2022). In addition, it directly impacts the individual's quality of life and their daily routine (work, study, leisure, among others), especially when diagnosis occurs in advanced stages (FERIOLI et al., 2018; LAZARUS; BAYS, 2022). Due to this characteristic, it is silent cancer that people usually discover in the advanced stage (QUEIROZ; ALEGRANCI et al., 2022; SCHULT et al., 2021). In Brazil, data from the INCA estimates 45,630 new cases of colorectal cancer for each year of the 2023-2025 triennium, with 21,970 for men and 23,660 for women (INCA, 2022). In 2023, 500 new cases will be estimated in the state of Mato Grosso and 140 new cases of CRC for the capital Cuiabá (INCA, 2022).

Cancer patients can be treated with different therapies, such as surgery, radiotherapy, and chemotherapy, subdivided into classical chemotherapy, immunotherapy, and hormone therapy (GANGGAYAH et al., 2019), (LEE et al., 2012). Most chemotherapy treatments for many primary cancers are administered to outpatients, so patients must be involved in self-management of the side effects and other problems related to the treatment at home (CHEONG et al., 2018). In the case of CRC, the treatment usually involves surgery to remove the primary tumor, locally compromised organs and structures, and identified metastasis, followed by chemotherapy to destroy the cancer cells that may have remained (BRASIL, 2003). Some adverse effects related to cancer treatment are fatigue, pain, appetite loss, dyspnea, vomiting, nausea, insomnia, constipation, and diarrhea (CARAYOL et al., 2019), (CHEONG et al., 2018), (SUN et al., 2017), (PARK et al., 2019). Thus, the use of technological features is encouraged to support patients in the treatment phase with the dissemination of information on common symptoms and adverse effects related to treatment, and how to minimize their impacts. Furthermore, technology has contributed to the multidisciplinary team in the diagnosis and treatment of patients.

Mobile health (mHealth) has been highlighted as an essential support tool in cancer management (SOH et al., 2018). mHealth is a tool that presents an opportunity to reach the

underserved population with educational information on health-related treatment and to encourage their participation in self-management programs (CHEONG et al., 2018). Wearable devices allow patient data collection in real-time and contribute, for example, to self-manage side effects by patients with cancer undergoing treatment (MILLSTINE et al., 2019). These devices are part of the context of the Internet of Things (IoT), which is a recent paradigm in information technology (QI et al., 2017), (SADOUGHI; BEHMANESH; SAYFOURI, 2020). IoT is reshaping healthcare and is a leading enabler for distributed healthcare applications; it allows remote monitoring on multiple fronts, allowing healthcare implementation in various environments, from long-term care of the elderly and home monitoring of patients to the development of more severe healthcare rehabilitation systems (ACETO; PERSICO; PESCAPÉ, 2020).

Studies evaluated the use of a wearable device and its association with adverse effects motivated by cancer treatment, surgery, chemotherapy, and/or radiotherapy (MILLSTINE et al., 2019), (CHEONG et al., 2018), (GRESHAM et al., 2018), (CARAYOL et al., 2019). Millstine et al. (MILLSTINE et al., 2019) demonstrated the feasibility of using interactive and portable electroencephalography to improve fatigue, quality of life, and stress in cancer patients during surgical treatment. Cheong et al. (CHEONG et al., 2018) assessed the use of mHealth and IoT through symptoms and nutritional monitoring, and a personalized rehabilitation program, to obtain results demonstrating the improvement of physical performance and the reduction of adverse effects during active chemotherapy treatment. Gresham et al. (GRESHAM et al., 2018) showed in patients with advanced cancer, using a wearable activity monitor, that increased physical activity reduced the chance of adverse effects, hospitalization, and the risk of death. Significant beneficial effects concerning fatigue, depression, anxiety, and quality of life were observed in patients undergoing active chemotherapy and subsequent radiation therapy and controlled by the armband and the accelerometer system (CARAYOL et al., 2019).

Several published surveys are available that cover different aspects of the application of IoT in healthcare (SADOUGHI; BEHMANESH; SAYFOURI, 2020), (DORRI et al., 2020), (RAMSEY et al., 2020), (KISS et al., 2019), (MCCANN; KATHRYN ANNE MCMILLAN; GEMMA PUGH, 2019), (SCHAFFER et al., 2019), (AYYOUBZADEH et al., 2020). For example, the review by Sadoughi et al. (SADOUGHI; BEHMANESH; SAYFOURI, 2020) identified and mapped the use of IoT in medicine. In Dorri et al. (DORRI et al., 2020), assessed the effects of physical activity interventions provided through eHealth on breast cancer patients. Ramsey et al. (RAMSEY et al., 2020) identified eHealth and mHealth interventions for youth undergoing cancer treatment, and child, adolescent, and young adult survivors of childhood

cancer. Schaffer et al. (SCHAFFER et al., 2019) identified randomized controlled trials to examine the feasibility of digital activity trackers in cancer survivors. Ayyoubzadeh et al. (AYYOUBZADEH et al., 2020) addressed which types of eHealth support have been provided to CRC survivors in the past two decades. In general, the reviews highlight that the use of IoT, mHealth, and eHealth to support cancer patients during treatment or healthcare is recent, and has been developing in the last 10 years, emphasizing the last 5 years. Several studies presently developed are experimental and pilot, and there are few randomized controlled trials from the literature available.

Studies also evaluated the use of conversational agents, called chatbots, in the health area (KATAOKA et al., 2021), (OH et al., 2020), (GREER et al., 2019), (CHAIX et al., 2019), (MONTENEGRO; DA COSTA; JANSSEN, 2022). Chatbots are Artificial Intelligence (AI) based conversation agents that interact with people through text messages (BIBAULT et al., 2019), (KATAOKA et al., 2021), (OH et al., 2020). Chatbot has proven to be a valuable and collaborative tool to reduce anxiety in young patients undergoing active cancer treatment (GREER et al., 2019). Chatbot proved viable to collect symptom data from elderly cancer patients undergoing chemotherapy treatment. The main symptoms identified were fatigue, abnormal sensitivity in the extremities, loss of appetite, and difficulty performing daily activities (PIAU et al., 2019). The solution also allowed text messages to inform other symptoms not treated by the questionnaire (PIAU et al., 2019). The chatbot contributed to improving medication adherence through reminders and educational content, and patients with breast cancer evaluated it very well (CHAIX et al., 2019).

1.1 Motivation

Based on the literature review, Queiroz et al. (QUEIROZ et al., 2021) observed several challenges in using IoT in treating cancer patients in active treatment. Some essential challenges observed were patient engagement, the instability and vulnerability of wearable devices, handling with technology, a homogeneous group of participants, and constant or periodic feedback. In addition, we also observed several challenges in the use of the conversational agent, such as technical literacy, adaptation and use by older people, interface, and integration with other technologies, such as electronic health records, medical documents, and sensors (PIAU et al., 2019), (MONTENEGRO; DA COSTA; DA ROSA RIGHI, 2019).

The main driver of the project is to improve patient engagement during the treatment phase through intelligent computational monitoring and periodic feedback. As a result, the

expectation is greater control and management of disease-related signs and symptoms and adverse effects related to the treatment, providing a better quality of life and reduced time to return to baseline.

In this way, the project has great potential for results and generating benefits for patients undergoing active cancer treatment. The proposed computational model, called Smart Monitoring Tool (SMT), consists of a text-based conversational agent, known as a chatbot, focused on passive and active patient monitoring, and a wearable device for monitoring physical activity.

1.2 Research Question and Hypothesis

The research question of this thesis is:

How can a computational model, based on the use of the Internet of Things and artificial intelligence, increase patient engagement during the active cancer treatment phase providing better monitoring of the patient's clinical condition?

The architecture of the computational model involves the creation of a conversational agent for interaction with the patient and the use of IoT techniques. To construct the conversational agent, we interviewed health professionals to map patients' main symptoms and adverse effects during the active treatment phase. We developed the chatbot using the Google Dialogflow platform based on this mapping. This platform has natural language processing capabilities and uses machine learning techniques to train pre-registered phrases. We expect to provide relevant information and guidance that collaborate and increase patient engagement in their treatment. In addition, the idea of the model is to provide individualized and automated feedback according to the patient's interaction with the chatbot.

IoT, including wearable devices, contributes to automated physical activity performance data collection. Patients undergoing cancer treatment are advised to perform physical activities regularly to lessen the effect of medications, strengthen their physical condition, and improve their clinical condition. The model encourages the patient to comply with medical recommendations for physical activities through notifications and reminders. In addition, the model provides chatbot integration with wearable devices so that the multidisciplinary team accompanying the patient has real-time access to the data collected. If a deterioration in your clinical condition is identified, the model notifies the multidisciplinary team.

Thus, we expect our research question to be answered during our study. Furthermore, as a research hypothesis, we have that the use of an intelligent computational model generates

greater engagement of colorectal cancer patients during active treatment and encourages them to maintain or improve their health and physical indicators to have a better quality of life and better management of symptoms and adverse effects related to treatment.

1.3 Objective

The main aim is to develop a new computational model for monitoring colorectal cancer patients in the active treatment phase using artificial intelligence and the Internet of Things. The following specific objectives were proposed:

- Perform a systematic review to identify the gaps related to the application of IoT in cancer patients.
- Develop a computational model that allows interaction between the patient and the multidisciplinary team, and the patient's self-care.
- Apply the computational model in the multidisciplinary team as a pilot study for the preliminary evaluation of the tool.
- Apply the computational model in colorectal cancer patients in stages I to IV.
- Evaluate the frequency of patient interactions with the SMT model, the use of the wearable device, the practice of physical activity performed, and the main symptoms and adverse effects reported.
- Evaluate the quality of life and the impact of treatment on the patient's life through surveys developed by the European Organization for Research and Treatment of Cancer.
- Analyze eating habits and physical activity practice before and after using the proposed model.
- Propose the development of a recommender system.

1.4 Document Organization

This thesis is structured in seven chapters. Chapter 1 refers to the introduction of the thesis, where we describe the work context, motivation, research question, and objectives. Chapter 2 presents the main definitions of the terms used in the thesis and how they relate to the work to be performed. Chapter 3 presents the state of the art of using the IoT, emphasizing wearable devices during the active treatment of cancer patients. We discuss the benefits, the main results, and the architecture used. In addition, we highlight the main challenges. Chapter

4 presents the proposed new model for monitoring and follow-up colorectal cancer patients in the active treatment phase. Chapter 5 describes the work's methodology, while Chapter 6 presents the results and discussions. Finally, Chapter 7 shows the conclusion, expected contributions, publications, and future work.

2 BACKGROUND

Several cancer patients may develop at least one chronic disease or signs and symptoms related to this condition, such as dyslipidemia, diabetes, osteoporosis, depression, anxiety, persistent fatigue, anemia, weight loss, headache, subsequent cancers, among others (LE et al., 2017), (CARLI et al., 2020), (CHUNG et al., 2019), (KLAAS et al., 2018), (ARGILÉS et al., 2018). Following data from the National Cancer Institute (INCA), Brazil is estimated to have 704,080 new cancer cases for each year of the 2023-2025 triennium, 483,000 if non-melanoma skin cancer cases are excluded (INCA, 2022). Cancer patients can be treated with different types of therapies, such as surgery, immunotherapy, chemotherapy, radiotherapy, and hormone therapy, depending on the stage of cancer and the patient's clinical condition (GANGGAYAH et al., 2019), (LEE et al., 2012).

Technology has helped the multidisciplinary team diagnose, monitor, and treat patients (QUEIROZ et al., 2021). Lifestyle changes, appropriate physical exercise, and the consumption of nutritional and supplementary foods are essential because they reduce adverse effects, mortality, and morbidity and improve the patient's quality of life (SOH et al., 2018). mHealth integrated with wearable devices can facilitate the patient's daily life and minimize the difficulties of self-care at home, providing a large amount of information (CHEONG et al., 2018), (MILLSTINE et al., 2019) and enabling the definition of individualized rehabilitation programs through the feedback generated by these technologies (CHEONG et al., 2018).

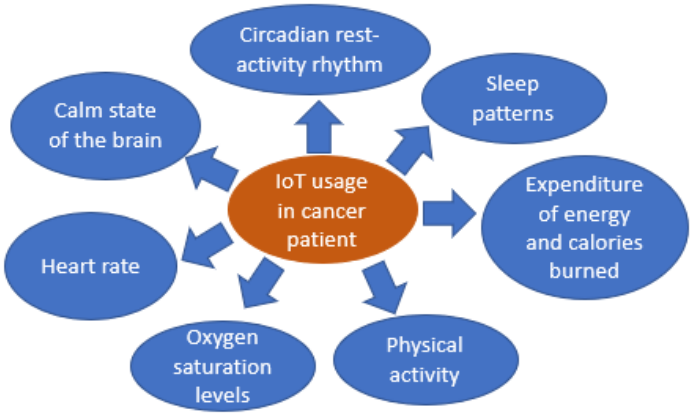
2.1 Internet of Things

IoT has emerged as a promising tool in healthcare and has the potential to reduce costs, improve user experience and patient monitoring, and increase the quality of life (COSTA et al., 2018), (GRALHA et al., 2022). This technology consists of interconnected objects with the ability to exchange and process information to improve patient health (COSTA et al., 2018). Its architecture considering the patient-centered view, involves 4 distinct layers: data acquisition through smart health objects, such as medical and wearable devices; storage of collected data; processing; and presentation of data in pre-defined contexts (COSTA et al., 2018). IoT combined with machine learning techniques has shown interesting results in processing vital signs to infer the risk of deterioration of the patient's clinical condition and optimize resources in hospitals by predicting future patient requirements (COSTA et al., 2018). Furthermore, these

techniques have the potential to be applied in various health contexts, such as monitoring cancer patients on active treatment while they are at home.

According to the literature, Queiroz et al. (QUEIROZ et al., 2021) demonstrated that the main information monitored by the IoT, including wearable devices, in cancer patients undergoing active treatment were: the calm state of the brain, heart rate, and oxygen saturation levels, physical activity, expenditure of energy and calories burned, sleep patterns, and the circadian rest-activity rhythm, as shown in Figure 1. The use of wearable devices showed significant results, such as IoT combined with personalized interventions have proven to be an efficient technique to improve the quality of life and mitigate adverse effects and symptoms related to cancer treatment (QUEIROZ et al., 2021). The use of wearable devices demonstrated that the improvement in physical activity correlated with a better clinical condition of the patient (QUEIROZ et al., 2021). Furthermore, sleep quality was associated with fatigue and interference with daily activity (QUEIROZ et al., 2021). A positive correlation between hemoglobin level with energy expenditure and physical activity was also observed (QUEIROZ et al., 2021). In general, the tools applied in the interventions were being used for the first time, which indicated that this was a recent issue and should be explored further (QUEIROZ et al., 2021). Some challenges and drawbacks in using IoT in cancer patients undergoing active treatment involve patient engagement, the instability and vulnerability of wearable devices, manual integration of collected data, handling with technology, relevant number of subjects, homogeneous group of participants, and constant or periodic feedback.

Figure 1: Main information monitored by the IoT, including wearable devices, in cancer patients undergoing active treatment.



2.2 Conversational Agent

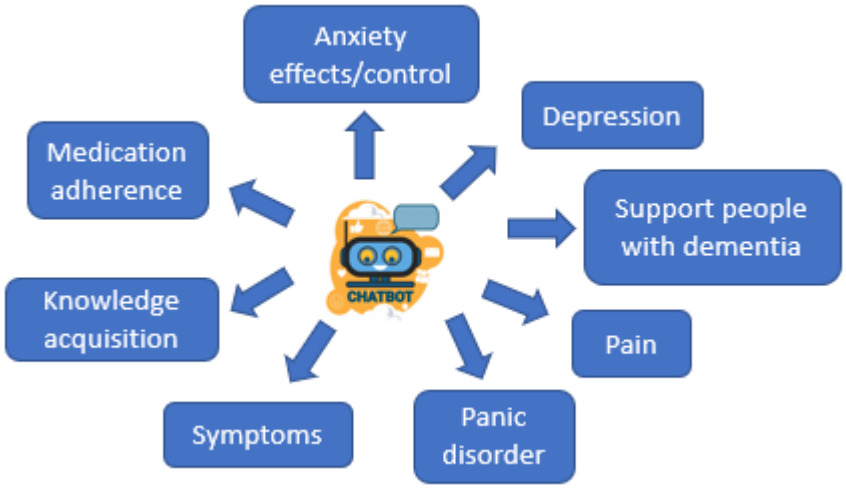
Conversational agents can help with patient follow-up during the active phase of treatment. Conversational agents use AI, including natural language processing and machine

learning to interact with humans (VALTOLINA; BARRICELLI; DI GAETANO, 2020). Natural language processing (NLP) is one of the main tools for interactions between humans and agents, mainly focused on signal processing and syntactic and semantic analysis of speech (MONTENEGRO; DA COSTA; DA ROSA RIGHI, 2019). The agents have been developed and enhanced to support healthcare professionals and the general public (MILNE-IVES et al., 2020). Based on the message sent by the user, the program, through AI, identifies the related categories (intents and entities), then activates the modules linked to these categories and, finally, composes and sends the responses to the users (BIBAULT et al., 2019), (KATAOKA et al., 2021), (OH et al., 2020), (CHAIX et al., 2019). Due to its scalability and accessibility, it can reach a large proportion of the population. It is a promising tool to support greater patient engagement in managing their treatments and contribute to advancing patient-centered care (MILNE-IVES et al., 2020).

The conversational agent is an essential tool to support cancer patients in active treatment. Most cancer patients are treated at home, needing to self-manage their treatment without close support from a medical team (CHAIX et al., 2019). According to the World Health Organization, at global health levels, treatment adherence is as crucial as the development of new drugs (CHAIX et al., 2019). However, patients' access to the health system is limited due to their social conditions, living in remote areas, and limited access to primary providers (PIAU et al., 2019), (CHEONG et al., 2018). Thus, in this context, technology can be an essential way to connect patients and medical staff.

Chatbots can be used as a virtual assistant performing and contributing to the reduction of anxiety effects/control (GREER et al., 2019), depression (FITZPATRICK; DARCY; VIERHILE, 2017), (INKSTER; SARDA; SUBRAMANIAN, 2018), pain (HAUSER-ULRICH et al., 2020), and panic disorder (OH et al., 2020); contribute to the identification of symptoms (PIAU et al., 2019); knowledge acquisition through educational content (KATAOKA et al., 2021), (CHAIX et al., 2019); assist in medication adherence (CHAIX et al., 2019); assist pregnant women during the prenatal and postnatal periods (MONTENEGRO; DA COSTA; JANSSEN, 2022); and support people with dementia (STARA et al., 2021), as shown in Figure 2. Chatbots must address issues that have significant impacts on users' health care. Their influence, however, depends on the acceptance and preference of users to use them instead of traditional alternatives (MILNE-IVES et al., 2020). Studies have highlighted participants' good acceptance of conversational agents (FITZPATRICK; DARCY; VIERHILE, 2017).

Figure 2: Examples of chatbot applications in healthcare.



A randomized study found that the satisfaction of breast cancer patients concerning the answers given about the therapy by the chatbot was as satisfactory as that of physicians. In addition, the study suggests that the chatbot can solve less complex patient doubts, avoiding the need for an appointment. Thus, doctors could spend more time treating patients who most need an appointment (BIBAULT et al., 2019). The use of a chatbot contributed to alleviating panic disorder (OH et al., 2020). Panic disorder severity and the level of social phobia significantly decreased in patients who used the chatbot, and the control of feeling helpless significantly increased compared to the control group (OH et al., 2020). Pas et al. (TE PAS et al., 2020) demonstrated that patients prefer to answer the questionnaires through the chatbot compared to answering conventionally on the computer. The chatbot was evaluated as more practical, efficient, innovative, fast, attractive, pleasurable, among others, by patients (TE PAS et al., 2020). Some studies, however, have shown some difficulties in implementing the chatbot, suggesting new and more comprehensive studies to confirm the results (HAUSER-ULRICH et al., 2020; KATAOKA et al., 2021).

Kataoka et al. (KATAOKA et al., 2021) evaluated the use of a chatbot incorporated into a social network to improve the knowledge of patients and their caregivers about the symptoms of lung cancer. However, due to the low level of user satisfaction, further studies should be carried out to improve the quality of responses and users acceptance (KATAOKA et al., 2021). Adherence to using a chatbot to support pain self-management by people with chronic pain was 71%. However, more than 70% of participants reported that the content of the messages needed to be deeper and indicated the need for a more significant number of messages (HAUSER-ULRICH et al., 2020). In addition, participants criticized the fact that the program does not allow free texts (HAUSER-ULRICH et al., 2020). Hauser-Ulrich et al. (HAUSER-ULRICH et

al., 2020) identified a significant relationship between the patient's intention to change behavior with his clinical deterioration due to pain and its intensity.

A systematic review reported recent advances in chatbot technology in medicine focusing on cancer therapy (XU et al., 2021). Xu et al. (XU et al., 2021) indicated that the chatbot has the potential to be integrated into medical practice, working together with healthcare professionals, contributing to cost reduction, and improving patient outcomes. Chatbots are applicable in healthcare that typically involve face-to-face interactions (XU et al., 2021). A pilot study aimed to evaluate the usage, usability, and perceived benefits of applying a chatbot that provides information on early detection of prostate cancer (GÖRTZ et al., 2023). Most patients experienced a clear to moderate increase in knowledge and indicated they would like to re-use the chatbot in the future and support using chatbots in clinical practice (GÖRTZ et al., 2023).

A retrospective observational study evaluated a chatbot's acceptance and user experience that automates hereditary cancer risk screening in women's self-care routines (NAZARETH et al., 2021). Most patients engaged with the chatbot, completed the cancer risk assessment, and concluded the genetic testing education section (NAZARETH et al., 2021). Results indicate that the chatbot addressed user expectations (NAZARETH et al., 2021).

Welch et al. developed a web-based chatbot to support users in collecting family health history and determining their risk for hereditary cancer. The authors also evaluated attracting users through marketing on social networks and websites (WELCH et al., 2020). Chatbot design focused on natural conversational human-to-human interaction (WELCH et al., 2020). All users received a personalized risk assessment report after completing the family health history report (WELCH et al., 2020). The results suggest that collecting family history information with a high level of engagement is possible (WELCH et al., 2020). However, the authors described the possibility that some fake data had been provided due to the discomfort caused by sharing personal data (WELCH et al., 2020).

Web-based chatbot contributed to screening for hereditary cancer syndrome in patients undergoing colonoscopy, and most patients who interacted with the tool completed the chat (HEALD et al., 2021). Internet-based chatbot developed to explain the radiotherapy treatment process to users was rated highly by users regarding navigability and quality of information (REBELO et al., 2022). Tawfik et al. demonstrated that breast cancer patients who used the chatbot had statistically less frequent, severe, and distressing physical and psychological symptoms than routine care and nurse-led education groups (TAWFIK et al., 2023). To the best

of our knowledge, this is the first work that contemplates the use of a text-based chatbot focused on colorectal cancer patients undergoing active treatment and which was applied in conjunction with the use of IoT.

2.3 Recommender System

Recommender systems have been widely studied in the last decade, and their application has generated benefits in several scenarios (SILVEIRA et al., 2019), (LU et al., 2015), (CHEUNG et al., 2019), (NARDUCCI; LOPS; SEMERARO, 2017). The recommender system aims to reduce information overload by suggesting to users the most relevant information and services in a large amount of data (LU et al., 2015), (ORMEL et al., 2021), (CHEUNG et al., 2019). It can be applied in several contexts, such as e-commerce, e-learning, e-business services, and healthcare (LU et al., 2015), (CAPPELLA; YANG; LEE, 2015), (NARDUCCI; LOPS; SEMERARO, 2017). One of the applications is in electronic commerce, where companies like Amazon use recommendation engines to present personalized recommendations to users to increase their sales (SILVEIRA et al., 2019), (CAPPELLA; YANG; LEE, 2015). In addition, other services such as Netflix and YouTube also use recommendation systems to encourage users to use the platform (SILVEIRA et al., 2019), (CAPPELLA; YANG; LEE, 2015), (GE et al., 2015).

Ormel et al. (ORMEL et al., 2021) developed and evaluated an application that recommends videos with experiential information for breast cancer patients undergoing surgery. The recommendation engine performs content-based matching by recommending videos of speakers with similar characteristics as the user (based on user profiles such as age, marital status, and profession) on topics selected by the user and through collaborative filtering (videos related to videos liked by the user and by similar users) (ORMEL et al., 2021). Sanchez Bocanegra et al. (SANCHEZ BOCANEGRA et al., 2017) assessed the feasibility of a content-based recommendation system that generates Medline Plus link recommendations from text extracted from metadata (titles, subtitles, and video descriptions) of selected YouTube videos in the areas of diabetes, hypertension, and general medicine. The system was evaluated by 26 recruited health professionals based on their familiarity with online health and health topics covered in the study (SANCHEZ BOCANEGRA et al., 2017).

Narducci et al. (NARDUCCI; LOPS; SEMERARO, 2017) developed a recommendation system using content-based and collaborative techniques embedded in a social

network to recommend health facilities (e.g., hospitals) or doctors consulted by patients with similar health status. The recommendation engine computes the similarity between patients based on the patient's profile – symptoms, conditions, and treatments – by exploiting health data shared by the community (NARDUCCI; LOPS; SEMERARO, 2017). A recommendation system using both knowledge-based and content-based techniques promotes recommended healthy diet plans for older people (ESPÍN; HURTADO; NOGUERA, 2016). Some information is required to produce the diet, such as physical properties, such as the nutritional status of the users; environmental factors; practice of exercises; allergies, contraindications, and dislikes; socioeconomics, culture, and religion (ESPÍN; HURTADO; NOGUERA, 2016). Ge et al. (GE et al., 2015) proposed a collaborative filtering recommender system using an extension of the Matrix Factorization rating prediction technique. Users were required to rate each recipe on a scale of 1 to 5 and associate tags to describe what influenced their rating (GE et al., 2015).

In this way, researchers have proposed personalized or non-personalized recommendations to design better recommendations that meet users' needs, encouraging them to consume more products and services (SILVEIRA et al., 2019). In non-personalized recommender systems, no user information is needed to make predictions. However, personalized recommenders require users' past consumption information to issue recommendations, which are more likely to meet the user's needs (SILVEIRA et al., 2019).

Commonly used recommendation techniques include collaborative filtering and content-based, as well as a combination of the two approaches (CHEUNG et al., 2019), (LU et al., 2015), (SANCHEZ BOCANEGRA et al., 2017), (NARDUCCI; LOPS; SEMERARO, 2017). Different recommendation methods result in different sets of recommended items for the end user, depending on the algorithm used (CHEUNG et al., 2019), (LU et al., 2015).

2.3.1 Content-based Recommendation Systems

The content-based recommendation predicts user preferences for new items based solely on the content similarity of previously rated items (SHARMA; SINGH AUJLA; BAJAJ, 2023), (SANCHEZ BOCANEGRA et al., 2017). For example, in the Netflix matrix, movies (items) are categorized (content characteristics) by genre, year of production, actors, directors, age rating, among others (CAPPELLA; YANG; LEE, 2015). This stored well-structured data helps identify items similar to those that received positive ratings from the target users and thus allows the system to recommend items closer to what meets the target user's interest (CAPPELLA; YANG; LEE, 2015). Analogously, in a matrix, each item is represented in rows, and the content

features in columns, each item is treated as a separate case, which is mathematically equivalent to a vector located in a high-dimensional feature space (CAPPELLA; YANG; LEE, 2015). However, recommendations within the collaborative filtering approach are not based on content features, but rather on item ratings by users and the similarity of item ratings by other users. Analogously, in a matrix, the evaluations of the items by the users are represented, with the users defined in rows and the items in columns. Evaluations can be performed in several ways, such as ratings on various scales, clicks, views, shares, among others (SHARMA; SINGH AUJLA; BAJAJ, 2023).

The advantage of content-based recommender systems is scalability (CAPPELLA; YANG; LEE, 2015). The construction of profiles of content characteristics can be coded and processed offline, which makes it possible to create them even before the system is made available to users, reducing computation time (CAPPELLA; YANG; LEE, 2015). However, a drawback is likely overspecialization due to the simple principle of recommending items similar to those preferred by the user in the past (CAPPELLA et al., 2015; LU et al., 2015).

2.3.2 Collaborative Filtering Recommendation Systems

Collaborative filtering (CF) can update recommendations according to user preferences and information consumption (SHARMA; SINGH AUJLA; BAJAJ, 2023). In this approach, the user's consumption of information can be compared to the consumption of other users who share similar interests and attributes, based on the condition that if a user with similar interests or features likes an item, the other will like it too (CHEUNG et al., 2019), (SANCHEZ BOCANEGRA et al., 2017). This allows for personalized recommendations for each user based on the user's own preferences and/or similarity to other users (CHEUNG et al., 2019), (SANCHEZ BOCANEGRA et al., 2017).

Collaborative filtering recommendation systems are based only on the evaluation of the items performed by the user; in this case, the profile mapping of the items' content characteristics is unexplored. Two CF subcategories have been broadly adopted: the k-nearest neighbor (k-NN) approach and the matrix factorization approach (CAPPELLA et al., 2015; CASILLO et al., 2022). k-NN works by identifying a pre-specified number ($n = k$) of items most similar to the items that were rated by the target user (item-based collaborative filtering) (CAPPELLA; YANG; LEE, 2015). Still, k-NN can work by identifying a pre-specified number ($n = k$) of users who share similar tastes to the target user, that is, users who positively evaluated items similar to the target user (user-based collaborative filtering) (CAPPELLA;

YANG; LEE, 2015). However, unlike k-NN approaches, CF using matrix factorization methods assume that the observed rating matrix is generated from an underlying linear model obtained through the vector product between user content preferences (U) and item content profile (I) (CAPPELLA et al., 2015; CASILLO et al., 2022; SANCHEZ BOCANEGRA et al., 2017). This linear model is similar to content-based recommendation algorithms; however, the difference lies in the fact that the exact dimensions along which item content could be characterized (hence user preferences as well) need to be inferred directly from the $U\ x\ I$ rating matrix without the aid of prior human or computer-assisted content coding (CAPPELLA; YANG; LEE, 2015).

Although the approach based on collaborative filtering brought innovations regarding the recommendations to the target user, it is unstable regarding the problem of sparse data (LU et al., 2015). It is vulnerable if there are little data target user's past ratings (sparseness) or, considering past ratings, if there are too few overlapping ratings recorded by raters (CAPPELLA et al., 2015; LU et al., 2015). Also, it cannot make recommendations for newly added items until they have been evaluated (CAPPELLA; YANG; LEE, 2015). Hybrid models encompassing content-based and collaborative filtering recommendation models are suggested to overcome these drawbacks (LU et al., 2015).

2.3.2.1 User-Base Algorithms

The user-based recommendation system is a collaborative filtering algorithm that looks for user taste similarities to make predictions (SHARMA; SINGH AUJLA; BAJAJ, 2023). The recommendation of items is based on similar user preferences. The algorithm considers that similar users are interested in the same items (ALMAZRO et al., 2010; SHARMA et al., 2023).

The algorithm is divided into 3 steps (ALMAZRO et al., 2010):

- 1st) Check the profile of all users to see which ones are similar to the target user;
- 2nd) Compute the union of these users' items and assign a weight according to their importance within the context; and
- 3rd) Select and recommend items that have the highest weight and have not yet been selected by the user.

The most essential step influencing performance is determining which users are similar to the target user (ALMAZRO et al., 2010). One of the methods used is the k-NN algorithm. This requires a training dataset and a well-categorized set of users (ALMAZRO et al., 2010). Then, the user's attributes are compared with those of other users in the training phase to

determine which are similar to him (ALMAZRO et al., 2010). Similarity can be calculated using Pearson's correlation, which can be explicit or implicit. In the explicit modality, users express the item ratings; however, on implicit evaluation, the evaluation of the item by the user occurs implicitly, for example through the time the user searches for the item, the number of times the user consults the item, clicks, share, among others (ALMAZRO et al., 2010). Similarity is calculated between users who rated the same items (ALMAZRO et al., 2010).

2.3.2.2 Item-Base Algorithms

Item-based recommender system is a collaboration filtering algorithm that looks for similarities between items to make a prediction (ALMAZRO et al., 2010). The expectation is that the user chooses items similar to items that have been highly rated by him in the past; thus, by analyzing the best-evaluated items, it is possible to have an idea of what the user wants in the future (ALMAZRO et al., 2010). The rating can be explicit, such as ratings on multiple scales, or implicit, such as clicks to view or download, viewing time (CAPPELLA; YANG; LEE, 2015), and ranking in item categories (ALMAZRO et al., 2010).

Compared to user-based algorithms, item-based algorithms are sparser and have good scalability. As a disadvantage, the cost of building the item x item matrix stands out; however, after doing so, the algorithm performs well and is scalable, standing out concerning the user-based one (ALMAZRO et al., 2010). Although slower, the user-based algorithm has been shown to produce more accurate recommendations than the item-based algorithm (ALMAZRO et al., 2010). The choice of approach depends on the business application. The advantage is that it is possible to simulate several methods, which helps to choose the most suitable one for your application (SHARMA; SINGH AUJLA; BAJAJ, 2023; TROUSSAS et al., 2023).

2.3.3 Challenges

If the proposed recommendations are based only on the evaluated items, then many good items still need to be evaluated are disregarded; this problem is called coverage metrics (ALMAZRO et al., 2010). Another challenge is the sparsity issue, which has few assessed items concerning the total volume of items (SHARMA et al., 2023; TROUSSAS et al., 2023). For newly established systems, they are undergoing a cold start, which makes them unable to make accurate recommendations since very few item ratings have been recorded (LU et al., 2015; SHARMA et al., 2023). Data redundancy, noise, and overfitting are other challenges for

recommendation engines (ALMAZRO et al., 2010; TROUSSAS et al., 2023). To reduce the scarcity problem, some researchers suggest using rewards to encourage users to rate outstanding items or capture implicit ratings based on user behavior (ALMAZRO et al., 2010).

3 RELATED WORK

This chapter presents a systematic review aimed to identify and describe the benefits of using IoT techniques on the quality of life and survival of cancer patients undergoing active treatment. This systematic review was published in the Journal of Biomedical Informatics in May 2021.

- QUEIROZ, D.A. de; COSTA, C.A. da; QUEIROZ, E.A.I.F. de; SILVEIRA, E.F. da; RIGHI, R.R. Internet of Things in active cancer Treatment: A systematic review. Journal of Biomedical Informatics, v. 118, n. May, 2021. DOI: https://doi.org/10.1016/j.jbi.2021.103814

3.1 Study design

This section discusses the research design and the steps which were used to accomplish this study. The work addresses the eligibility criteria, information sources, research questions, study selection, data collection process, and the article selection process.

3.2 Research questions

Research questions contribute to know the applications and the results obtained for the use of IoT techniques. Answers will enable us to consolidate the studies carried out on this topic and will make it possible to list which ones are the challenges and areas that need to be explored.

All questions proposed are related to the use of IoT technique during the treatment phase of cancer patients. Concerning general questions (GQ), question 1 addresses what has been consolidated in the treatment of cancer patients, and question 2 assesses what challenges are discussed in the literature.

Regarding specific questions (SQ), question 1 aims to discuss the main information monitored using IoT in the active treatment phase of cancer patients. Question 2 assesses the results obtained using this technique. Finally, question 3 investigates which systems and techniques are mostly used in architecture.

Answers to general and specific questions will be essential to answering the main question of the systematic review: How does the use of IoT impact the outcome of cancer patients undergoing treatment?

3.3 Search strategy

The search string definition process was carried out by searching scientific databases, correlating known terms, such as synonyms, acronyms, and word combinations within the context of the work. Furthermore, to certify the terms to be used in the search string, we also evaluate systematic reviews published as in (DEMIRIS et al., 2019), (WARRINGTON et al., 2019).

We used the PICOS approach proposed by (MOHER et al., 2009), (LIBERATI et al., 2009) to refine our research string. This is one of the suggested methods to support the definition of some subjects covered by PRISMA, such as objectives, search questions, and eligibility criteria, and each letter refers to a component: the participants (P), the interventions (I), comparisons (C), outcomes (O), and the study design chosen (MOHER et al., 2009), (LIBERATI et al., 2009).

- Participants: adult men and women (age 18 years or older); patient undergoing active cancer treatment (chemotherapy, surgery, or radiotherapy) or within 3 months of completing the treatment procedure.
- Intervention: use of IoT technique, including wearable electronic devices, to stimulate self-care, monitoring, and management in the phase treatment of cancer patients.
- Comparison: use of IoT to improve the quality of life of patients, the morbidity and mortality rate against the use of standard techniques to assist the cancer patient undergoing active treatment.
- Outcomes: improvement of quality of life, morbidity and mortality rate (anxiety, depression, clinical data, cachexia, anorexia, survival), and side effects (fatigue, distress, pain, nausea, diarrhea, and vomiting). Secondary outcomes include frequency of hospital emergency care, hospitalization, and reduced the caregiver's stress and depression.
- Study design: the review included non-randomized or randomized controlled clinical trials, cohort, pilot, observational, and feasibility studies. The patient's interaction with the IoT technique may have been automatic or manual.

In Figure 3, we demonstrated the search string defined to be used in querying the databases based on the search strategy.

To select the articles, studies (from the last 10 years, 2010-2020) were obtained from electronic databases and selected through searches using the search string. The electronic databases included in the survey were: Google Scholar, ACM, ScienceDirect, IEEE, JMIR, Springer, PubMed, CINAHL, Web of Science, and Wiley. We chose these databases because they are sources of relevant articles within the area covered in this paper, also, to providing full-text journals and conference proceedings of the most important health conferences involving patient self-care, IoT, cancer, wearable devices, and their relations.

Figure 3: Search string used for database queries.

Search String
("Internet of Things" OR "IoT" OR "Wearable" OR "Wearables") AND ("cancer patient" OR "cancer patients") AND "treatment" AND (("self-care") OR ("self-manage" OR "self-management") OR ("self-monitor" OR "self-monitoring"))

3.4 Article selection

In the article selection process, inclusion and exclusion criteria were defined as shown in Table 1 to ensure that the articles obtained were linked to the main objectives of the research. These criteria were proposed according to the terms defined in the intervention and participants in the PICOS method. We use the Mendeley Desktop as a reference management software to organize the selected articles and to carry out the selection process. All articles were reviewed by three reviewers independently, who verified their relevance to the scope of this review.

Table 1: Inclusion and exclusion criteria used in the article selection process.

Inclusion Criteria	Exclusion Criteria
• Articles that address studies with adult men and women • Interventions focused on patient undergoing active cancer treatment (chemotherapy, surgery, and/or radiotherapy) or within 3 months of completing treatment • Studies published in the last 10 years • Articles written in English	• Articles focused on children and adolescents (age up to 18 years) • Articles not related to primary studies (theses, dissertations, opinions, criticism, protocols, books, posters, abstracts, oral presentations, and reviews) • Articles that did not address the use of IoT technique, including wearable electronic devices, to stimulate self-care, monitoring, and management in the phase treatment of cancer patients

In the first stage, we removed duplicate articles. In the second stage, based on the abstracts of the articles, we removed those that did not meet the intervention and participants criteria. In this period, we also removed articles not related to primary studies (theses, dissertations, opinions, criticism, protocols, books, posters, abstracts, oral presentations, and reviews). In the second phase of excluding articles, we were conservative in removing studies if there were any doubts regarding the tools used in the intervention or scope. These articles

were also selected for the next stage. Only when the three reviewers confirmed that the article did not address the scope, it was excluded from the study.

In the third stage, based on reading the full article, we excluded articles that did not address the intervention, study design, and participants criteria. Moreover, the reviewers met to compare their article choices and discuss cases of disagreement. Subsequently, the reviewers, based on the mutual agreement, selected a final list of articles. If at least two reviewers assessed that the article did not address the scope, it was excluded from the study. To limit our search, we only considered articles published within the last 10 years (2010 to 2020) and written in English. The selection was made in April 2020.

3.5 Risk of bias

The risk of bias was independently assessed by two reviewers. To evaluate the included randomized controlled trials, the Cochrane Collaboration's tool proposed by (HIGGINS, JULIAN PT AND GREEN, 2011) was applied. The risk of bias for non-randomized studies was assessed using the Risk of Bias Assessment Tool for Non-randomized Studies (RoBANS) (DORRI et al., 2020), (KIM et al., 2013).

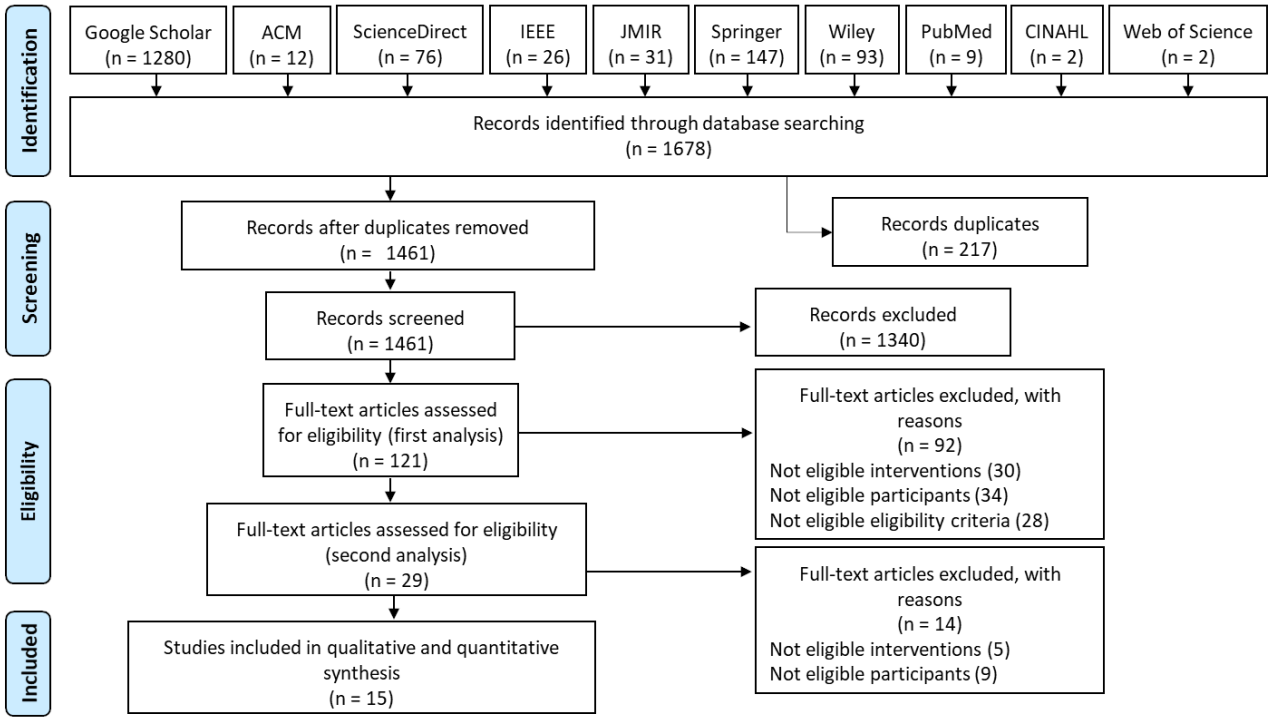
3.6 Results

The original search string returned 1,678 articles. First, we removed the duplicate articles (because the studies were available in more than one database), leaving 1,461 articles. In sequence, with the analysis of the articles based on the titles and abstracts, 1,340 articles were excluded, resulting in 121. In the third stage, based on the reading of the full text, 92 articles were excluded, leaving 29 papers. Finally, we performed the analysis of the pre-selected articles and concluded that 14 articles did not meet our scope, thus resulting in 15 selected papers. The complete process can be viewed in the PRISMA Flow Diagram in Figure 4. The 14 articles excluded in the second analysis of the full-text articles were briefly described in Table 2.

Several articles were eliminated during the abstract/title analysis because the papers did not apply IoT to patients undergoing active cancer treatment, focused on patients with completed cancer treatment, included children and adolescents (age up to 18 years), and/or were books, protocols, reviews, theses, dissertations, poster/abstracts, oral presentations, opinions, criticism. We also found that many of the studies dealt with cancer patients in the treatment

phase, but when restricted to the active treatment phase criteria, we noticed a large gap in this area, and the number of articles published with this focus was still low (Figure 4, Table 2 and Table 5). Thus, the selected articles demonstrate the importance, promising future, and challenges that exist in the use of IoT during active cancer treatment.

Figure 4: PRISMA flow diagram with the steps in the article selection process.



In accordance with the selected articles, it was observed that most cancer patients were elderly (mean age between 50 and 60 years) (PARK et al., 2019), (MILLSTINE et al., 2019), (CHEONG et al., 2018), (DROUIN et al., 2011), they presented breast cancer, were submitted to chemotherapy and surgery therapies and used IoT techniques, especially smartphones app and wearable devices (smartband, wristband, and armband) to stimulate your self-care, monitoring, and management during the active phase of treatment (CHUNG et al., 2019), (DREHER et al., 2019), (CARAYOL et al., 2019). Furthermore, it was demonstrated that the studies analyzed nutritional status (CHEONG et al., 2018) and physical exercise practice, heart rate, oxygen saturation levels (KADIRI et al., 2019), (CHEONG et al., 2018), sleep patterns (KOMARZYNSKI et al., 2019), (INNOMINATO et al., 2016), (INNOMINATO et al., 2018), and side effects of the patients mediated by the use of wearable electronic devices. The information collected by these articles demonstrated that the use of IoT significantly contributed to improving the patients' quality of life and efficiently improved the self-care and monitoring of these patients. Finally, the selected articles included 13 non-randomized and 02 randomized controlled trials.

Table 2: List of excluded articles in the second round of analysis carried out by the authors. The Intervention criterion is represented by column I and the Participants criterion by column P.

Identifier	Year	Study Design	Country	Type	Publisher	I	P
(CAI et al., 2020)	2020	Pilot Study	USA	Journal	Elsevier	X	
(O'CONNOR et al., 2020)	2020	Feasibility study	Ireland	Journal	Springer		X
(YEE et al., 2019)	2019	Pilot Randomized Controlled Trial	Australia	Journal	Elsevier		X
(JI et al., 2019)	2019	Prospective Clinical Trial	South Korea	Journal	JMIR		X
(MARTHICK et al., 2018)	2018	Cohort	Australia	Journal	JMIR		X
(BADE et al., 2018)	2018	Cohort	USA	Journal	SAGE		X
(SOH et al., 2018)	2018	Observational Study	South Korea	Journal	JMIR	X	
(RAMÍREZ et al., 2018)	2018	Cohort	USA	Journal	ACS Nano		X
(KLAAS et al., 2018)	2018	Observational Study	Switzerland	Journal	MDPI	X	
(GRESHAM et al., 2018)	2018	Cohort	USA	Journal	Nature		X
(GELL et al., 2017)	2017	Pilot study	USA	Journal	Springer		X
(LOUGHNEY et al., 2017)	2017	Pilot study	England	Journal	BMC		X
(KLAAS et al., 2017)	2017	Observational study	Switzerland	Conference	IEEE	X	
(SHINGLER et al., 2017)	2017	Qualitative study	England	Journal	BMC	X	

3.6.1 Article Quality

The analysis of the quality of the selected corpus is a highlight and concern in this review. Many reported studies are in the early design and maturation phase, and approximately 25% are randomized controlled trials (RCTs) or prospective observational studies.

Results of the methodological assessment are described in Table 3 and Table 4. Of the 15 studies included, 2 studies were RCTs (Table 3). In Carayol et al. (CARAYOL et al., 2019), the risk of bias was high concerning the item "Incomplete Outcome Data" due to the low compliance of the patients in the intervention group. The remaining thirteen non-randomized studies were assessed via RoBANS (Table 4). In the item "Incomplete Outcome Data", some articles had high risk due to the low compliance of the patients, and in (AMELI et al., 2017) the risk was high because the study included only 4 participants. In "Confounding Variables" the risk was high because the studies did not limit the patients' type of cancer (LAFARO et al., 2019), (KOMARZYNSKI et al., 2019), (CHEONG et al., 2018), (AMELI et al., 2017), (INNOMINATO et al., 2016). In "Selection of Participants" the risk rating was low because the study divided the participants into two groups (app group and class group) with the same characteristics and during the same period (KADIRI et al., 2019). In "Measurement of

Exposure", some studies were classified as high risk because some data were collected using self-reported methods without using structured interviews (KOMARZYNSKI et al., 2019), (PARK et al., 2019), (CHEONG et al., 2018).

Table 3: Risk of bias included in randomized controlled trials.

ID	Random Sequence Generation	Allocation Concealment	Blinding of Participants and Personnel	Blinding of Outcome Assessment	Incomplete Outcome Data	Selective Reporting	Other Bias'
(CARAYOL et al., 2019)	Low	Low	Low	Low	High	Low	Low
(MILLSTINE et al., 2019)	Low	Low	Low	Low	Low	Low	Low

Table 4: Risk of bias included in non-randomized controlled trials.

ID	Selection of Participants	Confounding variables	Measurement of exposure	Blinding of outcome assessments	Incomplete outcome data	Selective outcome reporting
(CHUNG et al., 2019)	High	Low	Low	Low	Low	Low
(KADIRI et al., 2019)	Low	Low	Low	Low	Low	Low
(DREHER et al., 2019)	High	Low	Low	Low	High	Low
(LAFARO et al., 2019)	High	High	Low	Low	Low	Low
(KOMARZYNSKI et al., 2019)	High	High	High	Low	Low	Low
(PARK et al., 2019)	High	Low	High	Low	Low	Low
(CHEONG et al., 2018)	High	High	High	Low	Low	Low
(INNOMINATO et al., 2018)	High	Low	Low	Low	High	Low
(NYROP et al., 2018)	High	Low	Low	Low	High	Low
(AMELI et al., 2017)	High	High	Low	Low	High	Low
(SUN et al., 2017)	High	Low	Low	Low	Low	Low
(INNOMINATO et al., 2016)	High	High	Low	Low	Low	Low
(DROUIN et al., 2011)	High	Low	Low	Low	High	Low

A point to highlight is that some recent studies were considered innovative, as the theme is recent and still has much to be explored (PARK et al., 2019), (CARAYOL et al., 2019), (KOMARZYNSKI et al., 2019), (CHEONG et al., 2018), (DREHER et al., 2019). Park et al. (PARK et al., 2019) published the first study that demonstrated the feasibility and efficacy of the smartphone app-based pulmonary rehabilitation for improving exercise capacity and symptoms in patients with advanced non–small cell lung cancer (NSCLC) during chemotherapy. Carayol et al. (CARAYOL et al., 2019) was the first study to demonstrate that an exercise-diet intervention delivered during breast cancer chemotherapy and radiotherapy had significant benefits on fatigue and quality of life that are sustainable 1 year after the end of the intervention (power and strength were measured by the accelerometer system and data about physical activity by the armband). Furthermore, Dreher et al. (DREHER et al., 2019) was the

first to evaluate adherence to Fitbit use during adjuvant or neo-adjuvant chemotherapy in patients with early breast cancer.

3.6.2 Research Questions

In this section, selected articles were analyzed based on the issues highlighted in section 3.2. The researched literature focused on applications of the use of wearable devices and IoT to assist the recovery process of patients with cancer undergoing active treatment, in addition, to reducing the adverse effects and symptoms related to treatment.

3.6.2.1 What is the state of the art related to the application of IoT during the treatment phase of cancer patients?

The selected articles demonstrated the potential use of IoT during the active treatment of cancer patients, associations between the use of wearable devices with the improvement of side effects, and demonstrated that the volume of publications in the last 5 years increased, which shows the interest of the scientific area and the relevance of the theme. Furthermore, the engagement of the patient during the period of intervention is a challenge, which generates the need for new strategies to ensure their permanence in the study, such as feedback, the possibility of monitoring their progress in real-time, individualized actions, and the involvement of specialists.

To obtain a better knowledge of the use of IoT in cancer patients undergoing active treatment was created a taxonomy, as shown in Figure 5. The taxonomy was organized in blocks, where each block represented a context for the use of IoT in the interventions and describes how the state of the art in the field is addressed. At the beginning, active treatment involved patients who were undergoing chemotherapy, radiotherapy, and/or surgery. Moreover, it was demonstrated that two groups of indicators were collected during the research, one group refers to objective indicators that involve collecting information without the intervention of patients through wearable devices, sensors, and smartphone app. The other group refers to subjective indicators that were collected through interviews and sessions conducted with experts, or a member of the research team, or questionnaires that were answered with or without the support of the project team. Furthermore, periodically, the data collected by the smartphone app, sensors, and wearable devices are integrated into the project team's database. This can occur automatically or manually with or without the support of the research member according

to a pre-defined periodicity. In addition, control points and feedback are important tools that enable the project team to monitor whether data is being collected correctly, to identify and correct problems during the intervention, to validate that the intervention is occurring as expected, and to verify that the use of the electronic devices was correct.

Figure 5: Taxonomy of the use of IoT in cancer patient undergoing active treatment.

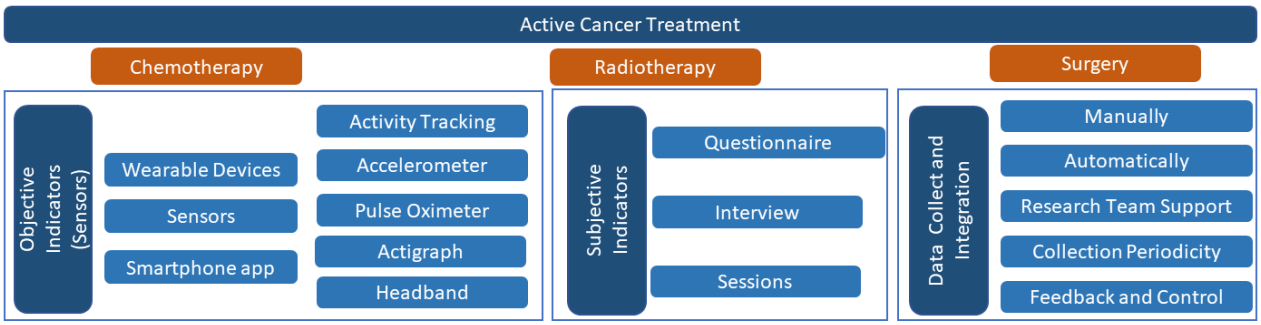


Table 5 lists the final corpus of articles published related to the search strategy, while Table 6 describes the main information about the selected articles, including the intervention applied and the main results obtained. This approach gives to the reader an overview of the relevance of the review and the articles considered in this research. The selected articles were realized in North America (USA), Europe (England and France), Asia (South Korea), and Oceania (Australia), however, in Latin and Central America and Africa, there have not been any studies, which shows a potential opportunity to explore this subject in future studies. To conclude, as described in Figure 4, we had two rounds of full reading of the articles. This was necessary because some articles left us with doubts as to whether they met the scope of the review. After the second round, 14 articles were excluded, as they did not address the intervention or participants' criteria as described in section 3.4. Table 2 shows the excluded articles and identifies which main criteria the articles did not address, intervention or participants.

3.6.2.2 What is the main information monitored by the IoT in the treatment of cancer patients?

According to the literature, the main information monitored by the IoT, including wearable devices, was the measurement of the calm state of the brain and its possible effects on fatigue, QoL, and stress in cancer patients (MILLSTINE et al., 2019), energy expenditure (DROUIN et al., 2011), continuous collection of heart rate and oxygen saturation levels during physical activity (KADIRI et al., 2019), (CHEONG et al., 2018), (PARK et al., 2019), and monitoring daily steps, walking distance, calories expended and sleep patterns in real time during the study period (Table 7) (CHUNG et al., 2019), (LAFARO et al., 2019), (SUN et al.,

2017), (CHEONG et al., 2018), (DREHER et al., 2019), (PARK et al., 2019), (NYROP et al., 2018), (KOMARZYNSKI et al., 2019). Moreover, a wrist-watch accelerometer was used to monitor the circadian rest-activity rhythm, 24 hours a day, in the home of patients who were undergoing chemotherapy (INNOMINATO et al., 2016), (INNOMINATO et al., 2018). In cases of lack of data transmission, greater than 24 hours, alert about high symptom severity, sudden bodyweight loss, or apparent deterioration of the rest-activity rhythm, the oncology nurse would phone the patient and organize any appropriate intervention required. The intervention, for example, could be a home visit by a technician or nurse, a referral to the patient's oncologist, an emergency visit to the outpatient clinic, or a hospital admission (INNOMINATO et al., 2016), (INNOMINATO et al., 2018).

Sensors distributed around the body were used to identify some significant gait patterns in the motion data indicative of chemotherapy effects on the physical performance status of the patient (AMELI et al., 2017). Between the beginning of the intervention and the end of chemotherapy and radiotherapy sessions, several variables were collected through an accelerometer, among them, the total duration of physical activity, the total duration of moderate physical activity (measured intensity from 3 to 6 METs), average metabolic equivalent of tasks (METs), and the sedentary time (less than 3 METs) (CARAYOL et al., 2019).

Table 5: Final corpus of articles published related to the search strategy.

Identifier	Year	Study Design	Country	Type	Publisher
(CHUNG et al., 2019)	2019	Observational Study	South Korea	Journal	JMIR
(KADIRI et al., 2019)	2019	Cohort	England	Journal	BMC
(DREHER et al., 2019)	2019	Pilot investigation	USA	Journal	Elsevier
(LAFARO et al., 2019)	2019	Pilot study	USA	Journal	Springer
(CARAYOL et al., 2019)	2019	Randomized Controlled Trial	France	Journal	BMC
(KOMARZYNSKI et al., 2019)	2019	Pilot study	France	Journal	OXFORD
(MILLSTINE et al., 2019)	2019	Randomized Controlled Trial	USA	Journal	SAGE
(PARK et al., 2019)	2019	Pilot Study	South Korea	Journal	JMIR
(CHEONG et al., 2018)	2018	Clinical Study	South Korea	Journal	Elsevier
(INNOMINATO et al., 2018)	2018	Pilot Study	France	Journal	JCO
(NYROP et al., 2018)	2018	Longitudinal, observational study	USA	Journal	Springer
(AMELI et al., 2017)	2017	Pilot Study	Australia	Journal	Elsevier
(SUN et al., 2017)	2017	Proof-of-concept pilot study	USA	Journal	JAMA
(INNOMINATO et al., 2016)	2016	Pilot study	France	Journal	JMIR
(DROUIN et al., 2011)	2011	Cohort	USA	Journal	Wolters Kluwer

Table 6: Intervention information and results of selected articles.

ID	Title	C*	Sample (duration)	Wearable Devices	Main Findings
(CHUNG et al., 2019)	An Assessment of Physical Activity Data Collected via a Smartphone App and a Smart Band in Breast Cancer Survivors: Observational Study	4	160 (6 months)	• Smart band (Fitbit Charge HR) and Fitbit app • Smartphone app (WalkOn app)	• The overall data collection rates for using a smartphone app and smart band were 88.05% and 52.45%, respectively. • Step counts collected via the smart band showed a negative correlation with distress level, and a positive correlation with self-reported sleep quality.
(KADIRI et al., 2019)	Fit 4 surgery, a bespoke app with biofeedback delivers rehabilitation at home before and after elective lung resection	2	65 (18 months)	• The Fit 4 Surgery app • Pulse oximeter	• The Global Health score at 5 months' post-surgery for the intervention group significantly increased and had returned to the baseline level. • Patients who used app and wearable device participated in more rehabilitation sessions than the class group during the preoperative and postoperative periods.
(DREHER et al., 2019)	Fitbit Usage in Patients With Breast Cancer Undergoing Chemotherapy	2	65 (9 months)	• Wristband (Fitbit Charge 2 or Fitbit HR)	• Adherence was negatively correlated with the timing of treatment and was lower among participants receiving neoadjuvant chemotherapy versus adjuvant chemotherapy. • The adherence to wearing the Fitbit was low over 9 months, with a mean number of valid days of 44.5% among participants who synced at least once.
(LAFARO et al., 2019)	Pilot study of a telehealth perioperative physical activity intervention for older adults with cancer and their caregivers	1	68 (8 months)	• Wristband pedometer (Vivofit 3; Garmin Ltd) • Session telehealth	• Preoperative patient adherence to wearable device use was 79%, and 68% post-discharge, and during hospitalization, gastrointestinal cancer patients had a lower number of daily steps than lung cancer patients. • Significant improvements in mean SPPB (short physical performance battery) score before surgery to 2–4 weeks post-discharge in lung and gastrointestinal cancer patients. • Functional capacity and mobility from baseline to post-discharge had no significant changes in cancer patients.
(CARAYOL et al., 2019)	Short- and long-term impact of adapted physical activity and diet counseling during adjuvant breast cancer therapy: the "APAD1" randomized controlled trial *APAD = Adapted Physical Activity and Diet	11	143 (18 months)	• Armband (SenseWear Pro) • Myotest® accelerometer system	• BMI and total fat mass were significantly reduced, and lower limb muscle endurance was significantly increased in APAD vs the control group at the end of radiotherapy. • The APAD group demonstrated a significant effect on the improvement of breast cancer patients in relation to fatigue and Global QoL at the end of chemotherapy and radiotherapy until the following 12 months compared to the control group. Anxiety and depression were significantly reduced at the end of chemotherapy and radiotherapy. • The objective measures performed by the accelerometer did not show a significant increase in intensity and moderate physical activity, unlike the proposed hypothesis.

(KOMARZYNSKI et al., 2019)	The day after: correlates of patient-reported outcomes with actigraphy-assessed sleep in cancer patients at home (inCASA project)	0	31 (30 days)	• Wrist-worn actigraph • Electronic inCASA platform	• The worsening of subjective sleep indicator was correlated with the lower sleep efficiency and the larger number of wake episodes. • The number of wake-up episodes measured objectively by actigraph had a statistical correlation with fatigue, drowsiness, and interference with activity. Sleep efficiency was only correlated with drowsiness.
(MILLSTINE et al., 2019)	Use of a Wearable EEG Headband as a Meditation Device for Women With Newly Diagnosed Breast Cancer: A Randomized Controlled Trial	1	30 (3 months)	• Wearable electroencephalographic device for meditation	• Demonstrated the feasibility of using interactive and portable electroencephalography to improve fatigue, quality of life, and stress in cancer patients undergoing surgical treatment. • The emotional and mental fatigue and vigor subscales reported by the intervention group participants improved significantly from baseline to post-surgery, and from baseline to 3 months after surgery.
(PARK et al., 2019)	Mobile Phone App-Based Pulmonary Rehabilitation for Chemotherapy-Treated Patients With Advanced Lung Cancer: Pilot Study	7	100 (12 weeks)	• Smart AfterCare app • Smartband (URBAN S) • Portable pulse oximeter • Resistance bands for physical therapy	• At the end of the intervention, the 6MWD (6-min walking distance), fatigue, appetite loss, diarrhea, and distress indices (anxiety, depression) significantly improved in the patients overall. The 6MWD of the patients with stable disease significantly improved at 6 weeks and 12 weeks. • Notifications were sent when the app had not been used for a period, as result 90% of patients completed the intervention.
(CHEONG et al., 2018)	Efficacy of Mobile Health Care Application and Wearable Device in Improvement of Physical Performance in Colorectal Cancer Patients Undergoing Chemotherapy	16	102 (12 weeks)	• Smartphone app • Wearable device (Urban S; Partron Co). • Hand-held dynamometer (upper extremity muscle strength)	• Significantly improved the physical functions (the lower extremity strength and cardiorespiratory endurance), significantly alleviated the symptoms (fatigue and nausea/vomiting) related to the cancer treatment, and improved the nutritional status of the patients
(INNOMINATO et al., 2018)	Home-Based e-Health Platform for Multidimensional Telemonitoring of Symptoms, Body Weight, Sleep, and Circadian Activity: Relevance for Chronomodulated Administration of Irinotecan, Fluorouracil-Leucovorin, and Oxaliplatin at Home—Results From a Pilot Study	14	11 (30 days)	• The inCASA platform • Wrist actigraphy (Micro MotionLogger)	• Compliance was 70% for actigraphy. • An increase in total sleep time (TST) was correlated with a decrease in insomnia and anorexia severity. TST was also correlated with an increase in interference with work and activity. • Insomnia patterns were inversely preceded by a deterioration of all actigraphy parameters (circadian dichotomy index - I<O, sleep efficiency, total sleep time, and sleep midpoint).
(NYROP et al., 2018)	Measuring and understanding adherence in a home-based exercise intervention during chemotherapy for early breast cancer	15	127 (12 weeks)	• Activity Tracker (Fitbit Zip)	• Improvement in fatigue, overall quality, and anxiety of life was correlated with a higher number of steps during chemotherapy; however, a smaller number of steps was correlated with reports of a higher number of chemotherapy-related symptoms such as severe/very severe. • Higher anxiety was inversely associated with step count during treatment.

(AMELI et al., 2017)	Objective clinical gait analysis using inertial sensors and six minute walking test	9	4 (4 weeks)	• 17 body-mounted sensors measuring the real-time variation of the position, velocity, acceleration, orientation, angular velocity, and angular acceleration of various body segments	• The unsupervised classification of motion data produced by inertial sensors detected the impact of fatigue induced by chemotherapy by analyzing the variation of kinematic data generated during 6MWT (six-minute walk test) and has the potential to be an objective method to evaluate the physical performance status (PPS) of cancer patients.
(SUN et al., 2017)	Wireless Monitoring Program of Patient-Centered Outcomes and Recovery Before and After Major Abdominal Cancer Surgery	17	20 (4 months)	• Wristband pedometers (Vivofit 2; GarminLtd)	• 88% of patients wore the pedometer for at least 3 days before surgery and during hospitalization. After discharge, 83% wore this device for at least 1 week. • Patients reported via online survey a return to baseline (preoperative) in terms of symptoms and quality of life, however, their mobility and number of daily steps measured via wristband pedometer remained worse compared to baseline, one-third of baseline (preoperative). • During the hospitalization and 1 week after discharge, the number of daily steps dramatically reduced compared to the preoperative period, with the corresponding worsening of symptom and quality of life scores. At week 2 after discharge, they had an improvement in both indicators. Indicating a potential correlation between the number of daily steps and Comprehensive Complication Index.
(INNOMINATO et al., 2016)	Clinical Relevance of the First Domomedicine Platform Securing Multidrug Chronotherapy Delivery in Metastatic Cancer Patients at Home: The inCASA European Project	12	31 (58 days)	• Wrist actigraphy (Micro MotionLogger) • inCASA platform	• Individual general compliance for the actigraphy parameter was 74.7%. • A daily rest-activity I<O values were observed over the 2 weeks preceding an unplanned hospitalization. • The proposed model with the combination of circadian rest-activity I<O parameter (relative percentage of activity in-bed versus out-of-bed), body-weight change, and MDASI scores obtained an accuracy of 94% to predict whether subsequent emergency hospitalization during the following 3 days was required.
(DROUIN et al., 2011)	Changes in Energy Expenditure, Physical Activity, and Hemoglobin Measures Associated with Fatigue Reports During Radiation Treatment for Breast Cancer: A Descriptive and Correlation Study	0	17 (6 weeks)	• Armbands (SenseWear® Pro-2 Body Monitoring System armbands)	• Energy expenditures (kcals per day) and physical activity (steps per day) as defined by the armbands had declined significantly between the fourth and sixth week of radiation treatment • Between the first and sixth week of treatment, fatigue scores negatively correlated with energy expenditure, and hemoglobin levels were positively correlated with energy expenditure and physical activity, suggesting that women with anemia have less calorie loss and a reduction in daily step count.

*The number of citations is represented by column C.

Most articles addressed patients undergoing chemotherapy and breast cancer. Table 7 showed an association between the collected data of the wearable devices, the type of treatment considered during the intervention, and the type of cancer.

Table 7: Association of the collected information with the type of treatment and the type of cancer of the patients who participated in the intervention. The reference article is represented by column R. *Patients and their caregivers participated in the study.

Collected Information	Type of Treatment	Type of Cancer	R
Calm state of the brain.	Surgery	Breast	(MILLSTINE et al., 2019)
Heart rate and oxygen. saturation levels.	Surgery	Lung	(KADIRI et al., 2019)
	Chemotherapy	Colorectal	(CHEONG et al., 2018)
	Chemotherapy	Lung	(PARK et al., 2019)
Monitor physical activity, energy expenditure, and calories burned.	Surgery	Breast	(CHUNG et al., 2019)
	Surgery	Gastrointestinal and Lung*	(LAFARO et al., 2019)
	Surgery	Hepatobiliary and Gastrointestinal	(SUN et al., 2017)
	Chemotherapy	Colorectal	(CHEONG et al., 2018)
	Chemotherapy	Breast	(DREHER et al., 2019)
	Chemotherapy	Lung	(PARK et al., 2019)
	Chemotherapy	Breast	(NYROP et al., 2018)
	Chemotherapy/Radiotherapy	Any histologically proven cancer type	(KOMARZYNSKI et al., 2019)
	Radiotherapy	Breast	(CARAYOL et al., 2019)
		Breast	(DROUIN et al., 2011)
Sleep patterns, monitor the circadian rest-activity rhythm	Surgery	Breast	(CHUNG et al., 2019)
	Chemotherapy	Breast	(DREHER et al., 2019)
	Chemotherapy	Any histologically proven cancer type	(KOMARZYNSKI et al., 2019)
	Chemotherapy	Any cancer type requiring chemotherapy	(INNOMINATO et al., 2016)
	Chemotherapy	Colorectal or Pancreatic	(INNOMINATO et al., 2018)
Identify significant gait patterns in the motion data indicative	Chemotherapy	Any cancer type undergoing chemotherapy	(AMELI et al., 2017)

3.6.2.3 What are the main results obtained with the use of IoT techniques during the treatment phase of cancer patients?

Concerning the interventions in patients undergoing surgery, studies have shown interesting results in which the interventions correlated with an improvement in physical activity, distress, and global health, as can be seen in Table 6 and Table 8. The step counts collected via a smart band showed a negative correlation with distress level and a positive correlation with self-reported sleep quality (CHUNG et al., 2019). The Global Health score at 5 months post-surgery for the intervention group significantly increased and had returned to

baseline level (KADIRI et al., 2019). Significant improvements in mean SPPB (short physical performance battery) score before surgery to 2–4 weeks post-discharge (LAFARO et al., 2019) were observed. The emotional and mental fatigue and vigor subscales reported by the participants improved significantly from baseline to post-surgery, and from baseline to 3 months after surgery (MILLSTINE et al., 2019). Important discordance between subjective and objective functional recovery was one of the findings in the study, which indicated the relevance of objective measures; in the second week after surgery, major abdominal cancer patients reported via online survey a return to baseline (preoperative) in terms of symptoms and QoL, however, their mobility and number of daily steps (one-third of preoperative baseline) measured via a wristband pedometer remained worse compared to baseline (SUN et al., 2017).

Table 8: Highlighted results in interventions with patients undergoing surgery, chemotherapy, or radiotherapy.

Treatment	Highlighted Results
Surgery	• Important discordance between subjective and objective functional recovery (SUN et al., 2017). • Better quality of sleep was associated with the greater number of daily steps (CHUNG et al., 2019). • The higher step counts associated with reduced distress data (CHUNG et al., 2019).
Chemotherapy	• Control of physical activities associated with improvement of the physical functions significantly alleviated the symptoms related to the cancer treatment and improved the nutritional status (CHEONG et al., 2018). • A temporal relationship was identified between the time course of the circadian rest-activity rhythm and fatigue reported by the patient, insomnia, and interference with activity or work on the following day (INNOMINATO et al., 2018). • The higher step counts associated with improved fatigue, overall quality of life, and anxiety (NYROP et al., 2018). • The smaller number of steps associated with a higher number of chemotherapy-related symptoms (NYROP et al., 2018). • The number of wake episodes measured had a statistical correlation with fatigue, drowsiness, and interference with activity (KOMARZYNSKI et al., 2019).
Radiotherapy	• Fatigue scores correlated negatively with energy expenditure (DROUIN et al., 2011). • Hemoglobin levels correlated positively with energy expenditure and physical activity (DROUIN et al., 2011).

For patients undergoing chemotherapy, studies showed interesting results in interventions correlated with improvement in physical activity, distress, and global health, as can be seen in Table 8. Cheong et al. (CHEONG et al., 2018) assessed in an individualized rehabilitation exercise program the performance of each individual using questionnaires and the IoT wearable device integrated with a mobile health application, which recorded the daily physical activities of the patients and a vital sign (heart rate). This solution significantly improved the physical functions (the lower extremity strength and cardiorespiratory endurance) and also significantly alleviated the symptoms (fatigue and nausea/vomiting) related to the cancer treatment, and improved the nutritional status of the patients (CHEONG et al., 2018).

Innominato et al. (INNOMINATO et al., 2018) identified a temporal relationship between the time course of the circadian rest-activity rhythm and fatigue reported by the patient, insomnia, and interference with activity or work on the following day. Patients who completed the pulmonary rehabilitation program significantly improved 6MWD, fatigue, appetite loss, diarrhea, and distress indices (anxiety, depression) (PARK et al., 2019). Improvement in fatigue, overall quality of life, and anxiety was correlated with a higher number of steps measured by Fitbit; however, a smaller number of steps was correlated with reports of a higher number of chemotherapy-related symptoms such as severe/very severe (NYROP et al., 2018). Unsupervised classification of motion data produced by inertial sensors detected the impact of fatigue induced by chemotherapy by analyzing the variation of kinematic data generated during 6MWT and has the potential to be an objective method to evaluate the physical performance status (PPS) of cancer patients (AMELI et al., 2017). In relation to sleep quality, Komarzynski et al. (KOMARZYNSKI et al., 2019) indicated that the number of wake-up episodes measured objectively by an actigraph had a statistical correlation with fatigue, drowsiness, and interference with activity. In addition, the worsening of the subjective sleep indicator was correlated with the lower sleep efficiency and the larger number of wake episodes (KOMARZYNSKI et al., 2019).

For patients undergoing radiotherapy, one of the findings of the study was energy expenditures and physical activity, as defined by the armbands, had declined significantly between the fourth and sixth week of radiation treatment (DROUIN et al., 2011), as shown in Table 8. Indeed, between the first and sixth week of treatment, fatigue scores correlated significantly and negatively with energy expenditure, and hemoglobin levels correlated positively with energy expenditure and physical activity, suggesting that women with anemia have less calorie loss and reduction in daily step count (DROUIN et al., 2011).

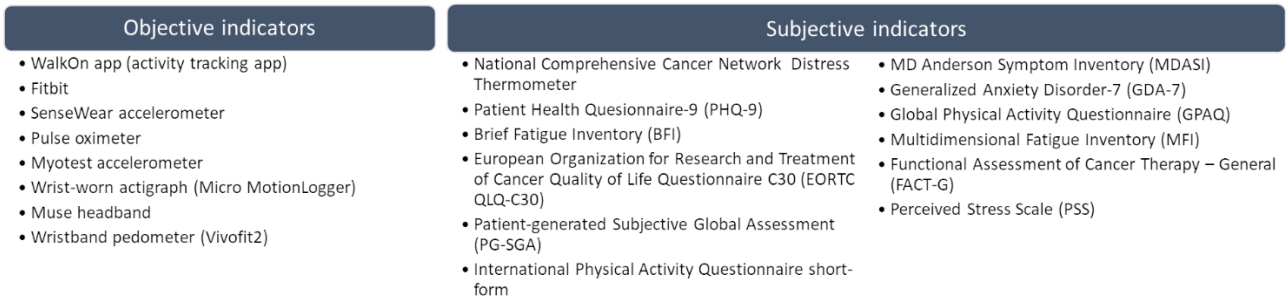
Lastly, interesting results have also been demonstrated during interventions comprising chemotherapy and radiotherapy. In (CARAYOL et al., 2019), the diet-exercise intervention demonstrated a significant effect on the improvement of breast cancer patients in relation to fatigue and Global QoL at the end of chemotherapy and radiotherapy until the following 12 months compared to the control group. The objective measures performed by the accelerometer, however, did not show a significant increase in intensity and moderate physical activity, unlike the proposed hypothesis (CARAYOL et al., 2019).

3.6.2.4 In terms of architecture, what are the main systems and techniques used?

According to the literature, the patient is the central and main icon of the architecture. Tools are usually used to extract subjective and objective indicators. Data collection and the integration of data with the research database occurs through a manual or automatic process, which may or may not be mediated with the support of a member of the research team.

Besides, Figure 6 shows some examples of tools used to collect objective and subjective indicators. In relation to objective indicators, several tools can be uses, such as WalkOn app, Fitbit, SenseWear, among others. In relation to subjective indicators, forms and questionnaires are usually used, which are made available through either electronic and paper processes, or individual interviews to collect information about the patients' clinical and physical status.

Figure 6: Examples of objective and subjective indicators used in the studies.



Interventions usually occur with the loan of wearable devices, where the data collected by the device is integrated into the app installed on the participant's smartphone. Some studies use their applications or systems to complement and consolidate the data collected by one or more wearable devices. Generally, in interventions, subjects need to complete questionnaires at the beginning of the intervention, baseline, and periodically according to the periodicity defined by the study protocol. The data collected in an automated process are called objective indicators, and the data collected through the responses to the questionnaires are subjective indicators. Several articles have been published describing these main systems and techniques used in terms of architecture (CHUNG et al., 2019), (CHEONG et al., 2018), (KADIRI et al., 2019), (DROUIN et al., 2011).

Participants who underwent surgery received wearable devices to monitor the physical activity, sleep patterns, heart rate, and oxygen saturation levels (CHUNG et al., 2019), (KADIRI et al., 2019), (LAFARO et al., 2019), (SUN et al., 2017), and to measure the calm state of the brain (MILLSTINE et al., 2019), as objective indicators. The calm state of the brain was measured using sensors that provided electroencephalographic data (MILLSTINE et al., 2019). In general, data were collected periodically before surgery, during hospitalization, and/or

after discharge according to the study protocol, and were synchronized automatically or manually into the central database. The patients received orientation about the use of the devices. Collected data were analyzed by the project team and evaluated during the study and/or at the end of the intervention. The subjective indicators were completed before surgery, during hospitalization, at hospital discharge, and/or post-discharge through either electronic and paper processes, or individual interviews conducted with the project team. Project members received an e-mail alert when the score defined by the patient in the survey was moderate to severe concerning symptoms and quality of life (SUN et al., 2017). Patients received reminder notifications when they did not respond to questionnaires (CHUNG et al., 2019).

Also, apps were installed on the patient's smartphone to collect more information and provide more functionality (CHUNG et al., 2019), (KADIRI et al., 2019). To promote health-related activities and motivate the patients undergoing surgery to participate in the intervention, the app enabled the creation of a mobile community whereby users could view the data of the daily steps collected, and share this with other members of the community (CHUNG et al., 2019). The app had exercises proposed for the intervention period. These exercises were demonstrated through video clips, where users were encouraged to perform each exercise for at least 3 minutes. At the end of each exercise session, the users received feedback on average oxygen saturation, exercise duration period, and whether they reached their heart rate target (KADIRI et al., 2019).

Participants who underwent chemotherapy received wearable devices to monitor the physical activity, physical functions, sleep patterns, heart rate, and oxygen saturation levels (CHEONG et al., 2018), (INNOMINATO et al., 2018), (NYROP et al., 2018), (PARK et al., 2019), (DREHER et al., 2019), (KOMARZYNSKI et al., 2019), and to identify some significant gait patterns in the motion data (AMELI et al., 2017), as objective indicators. The devices were delivered to patients at the beginning of treatment or in the first chemotherapy session. The collected data were transmitted daily or on the days scheduled to undergo chemotherapy to the research database by the patients (NYROP et al., 2018), (KOMARZYNSKI et al., 2019), (INNOMINATO et al., 2018). The objective was to assess and identify the correlations between objective indicators, such as the number of daily steps, walking distance, heart rate, and sleep efficiency; and subjective indicators, such as fatigue, quality of life, and anxiety. In general, patients were instructed to use wearable devices at home in the interval between chemotherapy sessions. In (PARK et al., 2019), on session days, patients were subjected to physical tests (e.g. 6MWT) to assess their clinical condition, and in (PARK et al., 2019), (NYROP et al., 2018) answered questionnaires under the guidance of the research team.

In some interventions, apps were installed and configured on patients' smartphones. The apps had several functions, among them, animation videos of the proposed exercises, and this was integrated with the wearable device (PARK et al., 2019). They had a to-do list that included daily tasks to be performed, such as taking medication and scheduling hospital visits; they had access to individual health information, such as the patients' laboratory results, information about the chemotherapy protocol, and general information about the treatment and its side effects; and had an in-app chat service that allowed interaction with the specialists (PARK et al., 2019), (CHEONG et al., 2018). Notifications were sent to the subjects when the app was not been used to encourage people to maintain the discipline and regularity of the proposed activities (PARK et al., 2019). The app also included questionnaires for subjective measurement of patients' clinical and physical data (CHEONG et al., 2018), or patients filled out questionnaires through either electronic and paper processes or individual interviews conducted with the project team (NYROP et al., 2018). The subjective indicators were completed at the beginning of treatment and during the treatment phase (NYROP et al., 2018), (PARK et al., 2019), (KOMARZYNSKI et al., 2019).

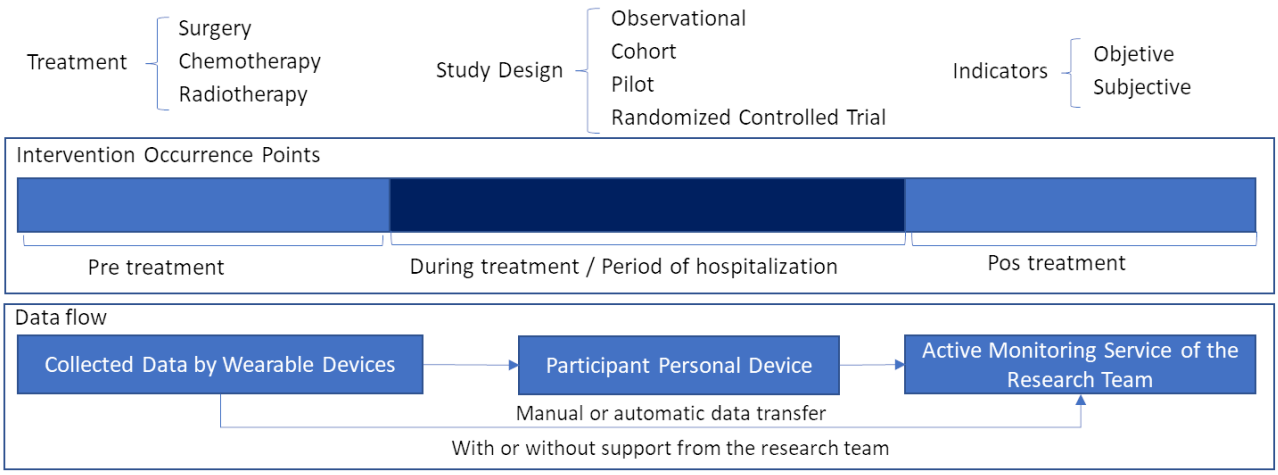
Participants who underwent radiotherapy received wearable devices to monitor the physical activity and energy expenditures (DROUIN et al., 2011), (CARAYOL et al., 2019). Data were collected periodically during radiation treatment (DROUIN et al., 2011), or both before starting chemotherapy and at the end of radiation therapy (CARAYOL et al., 2019). The data were transmitted to the computer by the research member in the radiotherapy session that immediately occurred after the data collection period (DROUIN et al., 2011). The subjective indicators were measured weekly by the nurse investigators from the first week to the end of the radiation treatment (DROUIN et al., 2011), or at all assessment times proposed by the intervention (start and end of chemotherapy, end of radiotherapy, 6 months and 12 months after the end of radiotherapy) (CARAYOL et al., 2019).

Figure 7 presents an overview of the main architectural aspects of the selected articles, where studies happened pre-, during, or immediately post-treatment. In surgery, the protocols covered the period before surgery, during hospitalization, and/or after discharge. In the case of radiotherapy and chemotherapy, once patients were submitted to several sessions of treatment, the interventions occurred throughout that period. Periodically, the data collected by the wearable devices were integrated into the project team's database.

3.6.2.5 What are the challenges related to the application of IoT in the treatment phase of cancer patients?

There were many challenges in the study of the application of IoT in patients undergoing active cancer treatment. The difficulty of getting a group of homogeneous patients (KOMARZYNSKI et al., 2019), (SUN et al., 2017), the lack of handling of patients with the technology (LAFARO et al., 2019), (CHUNG et al., 2019), the lack of constant or periodic feedback during the studies (KADIRI et al., 2019), (DREHER et al., 2019), (PARK et al., 2019), the patient engagement (KADIRI et al., 2019), (MILLSTINE et al., 2019), the limitation of getting a relevant number of participants (AMELI et al., 2017), (KOMARZYNSKI et al., 2019), (SUN et al., 2017), the manual integration of the data collected with the server (KADIRI et al., 2019), (SUN et al., 2017), (INNOMINATO et al., 2016), and the instability and vulnerability of wearable devices (QI et al., 2017), (NYROP et al., 2018), (ACETO; PERSICO; PESCAPÉ, 2020), (INNOMINATO et al., 2016) were some of the challenges found in the studies.

Figure 7: Overview of the main architecture aspects of the selected studies. At the top are presented the types of treatment, study design, and indicators. In the middle are shown the points where interventions occur. Finally, at the bottom, the data flow is shown from data collection to integration with the research team's active monitoring system.



3.7 Discussion

In accordance with the selected articles, it was observed that studies involving the application of IoT in medicine commenced receiving more attention from the scientific community in the last 10 years, with a greater emphasis in the last 5 years. Furthermore, it was observed that a small number of studies demonstrating the application of IoT in cancer patients undergoing active treatment was published in the last decade. Our results demonstrated that

most cancer patients who participated in the studies were elderly (mean age between 50 and 60 years) (PARK et al., 2019), (MILLSTINE et al., 2019), (CHEONG et al., 2018), (DROUIN et al., 2011), presented breast cancer, were submitted to chemotherapy and surgery therapies and used especially smartphones app and wearable devices (smartband, wristband, and armband) to stimulate your self-care, monitoring, and management during the active treatment (CHUNG et al., 2019), (DREHER et al., 2019), (CARAYOL et al., 2019). Several functions and symptoms were monitored by wearable electronic devices, resulting in significant beneficial effects to the patients contributing to their treatment and clinical condition. Finally, the selected articles included 13 non-randomized and 02 randomized controlled trials.

Similarly, Sadoughi et al. (SADOUGHI; BEHMANESH; SAYFOURI, 2020) identified that more than 70% of IoT studies in medicine are laboratory-based experiments, prototyping, pilot, and usability evaluation studies, with most studies published between 2016 to 2018. The authors also mapped out that IoT applications have scarcely been developed and implemented for diseases with a high mortality rate (e.g., chronic respiratory diseases and cancers). Kiss et al. (KISS et al., 2019) demonstrated that 16 randomized controlled trials of interventions addressing technology-supported self-guided nutrition and physical activity were identified, and only two of these studies were related to cancer patients undergoing active treatment, one using a wearable device.

The application of IoT, including wearable devices, has shown to be excellent tools to support cancer patients undergoing treatment. Aceto et al. (ACETO; PERSICO; PESCAPÉ, 2020) demonstrated the beneficial effects that the personalized rehabilitation programs bring to the patients' quality of life and cost savings for the self-care system. The use of IoT encourages patients to improve their physical conditioning and allows collecting information on the patient’s clinical status in real time, thereby directly impacting on the improvement of the adverse effects and symptoms resulting from the treatment. In selected studies, the main information monitored objectively was observed to be: a calm state of the brain, heart rate, oxygen saturation levels, physical activity, sleep patterns, and circadian rest-activity rhythm (MILLSTINE et al., 2019), (KADIRI et al., 2019), (PARK et al., 2019), (CHUNG et al., 2019), (LAFARO et al., 2019), (DREHER et al., 2019), (DROUIN et al., 2011), (KOMARZYNSKI et al., 2019), (AMELI et al., 2017).

Similarly, some literature reviews corroborated to the results of this survey, however, the studies did not cover patients only in the active phase of treatment. Dorri et al. (DORRI et al., 2020) highlighted that the use of eHealth contributed to the improvement of physical activity in breast cancer patients. Kiss et al. (KISS et al., 2019) observed that short-term technology-

supported self-guided interventions contributed to improve physical activity, fatigue, dietary behavior and health-related quality of life in cancer patients. The selected studies by McCann et al. (MCCANN; KATHRYN ANNE MCMILLAN; GEMMA PUGH, 2019) that contemplated the use of a wearable device to track the physical activity of cancer patients, reported an increase in physical activity following the intervention.

The results are promising, and further studies are needed to reproduce the findings and evaluate new possible approaches to the use of wearable devices. Moreover, another relevant point identified in the selected article is the discordance between subjective and objective functional recovery, which indicate the relevance of an objective measure performed by the wearable device (SUN et al., 2017). Also, it was possible to observe the significant contribution that the use of IoT brings to patients under cancer treatment, independently of the therapy type used.

In addition, in the systematic review, we observed that the subjective indicators were predominantly collected using questionnaires, and forms, and through these indicators, the level of symptoms and adverse effects related to treatment, quality of life, performance of physical activity, among others, were evaluated. The patients' distress was assessed using the National Comprehensive Cancer Network Distress Thermometer (CHUNG et al., 2019), (CHEONG et al., 2018); the presence of depressive symptoms was assessed using the Patient Health Questionnaire-9 (PHQ-9) (CHUNG et al., 2019), (PARK et al., 2019); the fatigue level was evaluated using the Multidimensional Fatigue Inventory and Brief Fatigue Inventory (CARAYOL et al., 2019), (MILLSTINE et al., 2019), (DROUIN et al., 2011); the general health-related quality of life was assessed using the European Organization for Research and Treatment of Cancer Quality of Life Questionnaire C30 (CHEONG et al., 2018), (KADIRI et al., 2019), (PARK et al., 2019), (CARAYOL et al., 2019); and symptom severity and symptom interference with activities were assessed using the MD Anderson Symptom Inventory (INNOMINATO et al., 2018), (LAFARO et al., 2019), (SUN et al., 2017). These indicators support and motivate reflection and self-analysis by patients, as well as the results are correlated with each other and with the objective indicators measured by wearable devices.

In accordance with the selected articles, several difficulties should be overcome. Regarding the lack of skills with the technology, Lafaro et al. (LAFARO et al., 2019) showed that the use of a smartphone app and a wearable device was feasible and accepted by elderly patients. In many cases, however, the challenge identified was to maintain the use of the wearable devices by the elderly for the entire period of the intervention. Chung et al. (CHUNG et al., 2019) suggested that low compliance was due to discomfort. Thus, it is possible to

observe that the use of a wearable device can be a drawback for patients' self-care since many have difficulties in handling the devices at home and do not have close people who can collaborate. The devices can still have some technical problems that leave them inoperative for a period and, therefore, important data are no longer collected by users.

The importance of monitoring to verify that wearable devices are functioning correctly was highlighted (QI et al., 2017). If this is not done, an inoperative device can be detected, however, only at the end of the intervention, which makes corrective measures impossible, impacting in the results (NYROP et al., 2018). Energy is one of the technical challenges encountered and is necessary to think in solutions to optimize its use to reduce unnecessary expenditure (ACETO; PERSICO; PESCAPÉ, 2020). According to Innominato et al. (INNOMINATO et al., 2016), the most common reasons for missing data reported informally, except for planned or emergency hospitalizations, were technical problems, out-of-home trips, forgetfulness, or patient malaise. Finally, the importance of constant monitoring by the project team is fundamental to the success of the research. Users may find it difficult to certify that the equipment is working correctly.

Concerning homogeneous or heterogeneous groups of patients involved, the results cannot be generalized and are limited due to the heterogeneity of the population. Thus, it is suggested that the studies include subjects with similar clinical and social characteristics. Lafaro et al. (LAFARO et al., 2019) and Komarzynski et al. (KOMARZYNSKI et al., 2019) suggested that the results obtained are limited due to the heterogeneous target audience regarding, for example, cancer type, stage, or treatment, which may involve different profiles of risks and complications. Feedback, reminders, and continuous monitoring of the collected data are interesting strategies to be adopted in the studies to encourage greater adherence and retain a greater number of participants during the studies. Kadiri et al. (KADIRI et al., 2019) suggested the incorporation of behavioral theories and techniques, as well as individualized feedback to improve compliance. The use of wearable devices may be greater when incorporate reminders or interventions to increase wear time or sync rates (DREHER et al., 2019), (PARK et al., 2019). Chemotherapy is generally a stressful period and with no reminders through calls, messages, and e-mails, the use of wearable devices by patients may not be their priority (DREHER et al., 2019).

Another important drawback is that most information is based upon pilot, observational, or feasibility studies, where the number of participants is low due to the study’s characteristics. The challenge here is to expand the study with a larger number of participants, including enabling a randomized controlled trial. Ameli et al. (AMELI et al., 2017) proposed to include

a larger number of cancer patients in future studies for complete clinical validation to be performed. Komarzynski et al. (KOMARZYNSKI et al., 2019) and Sun et al. (SUN et al., 2017) also highlighted as a limitation the small sample size. In this context, Sadoughi et al. (SADOUGHI; BEHMANESH; SAYFOURI, 2020) and Dorri et al. (DORRI et al., 2020) highlighted that most of the published studies reported small sample size, and were laboratory-based experiments, prototyping, pilot, or usability evaluation studies. In addition, the heterogeneity between the selected articles, such as in terms of sample size, study design and duration, and population characteristics, restricted the generalization of the results found (KISS et al., 2019), (MCCANN; KATHRYN ANNE MCMILLAN; GEMMA PUGH, 2019), (SCHAFFER et al., 2019).

Regarding patient engagement, some factors can directly impact performance, including the type and adverse effects of treatment, the severity of the clinical condition, and the age of the patient. In general, the use of wearable devices is usually well accepted by patients (SUN et al., 2017), (DROUIN et al., 2011), (PARK et al., 2019). Participants in the intervention group have more active participation than in the control group (KADIRI et al., 2019), (MILLSTINE et al., 2019). Besides, patient engagement is greater with the use of technologies, generating greater benefits and the acceptance of the intervention (KADIRI et al., 2019), (MILLSTINE et al., 2019). According to Kadiri et al. (KADIRI et al., 2019), patients who used an app and a wearable device participated in more rehabilitation sessions than the class group during the pre-operative and post-operative periods, demonstrating the feasibility of the intervention, acceptability, and compliance of patients.

As the considered studies have indicated, there are still many challenges in the application of IoT in cancer patients in the active phase of treatment and new studies should be addressed. We especially highlight two challenges, engagement, and feedback, as the topics to be addressed by our thesis. We aim is to develop a new computational model for monitoring colorectal cancer patients using artificial intelligence and the IoT that contributes to greater engagement from cancer patient during the active phase of treatment. In addition, the model aims to preventively identify the deterioration of the patient's clinical condition through the interactions that the patient is encouraged to perform within the proposed architecture.

We believe that the combination of the IoT and the chatbot can contribute to improving communication between the patient and the medical team during the periods between chemotherapy sessions. In addition, we believe that we also improve patient engagement with their own treatment. Studies have shown the chatbot as a useful tool for different applications related to cancer patients, such as educational content (KATAOKA et al., 2021), (CHAIX et

al., 2019), identification of symptoms (PIAU et al., 2019), and adherence to medication (CHAIX et al., 2019). In the next session we present the model conceptually, and how it helps patients to have a more active participation during their treatment. Furthermore, in this thesis, experiments based on the proposed architecture are foreseen.

The model acts mainly between periods of chemotherapy sessions and encourages the more assertive participation of the clinic's specialist team. During this period, the symptoms and adverse effects perceived by patients and the practice of physical activity are monitored. Furthermore, patients constantly receive feedback based on their reports and personalized feedback in case a deterioration of their clinical condition is identified, providing better health care.

4 SMART MONITORING TOOL (SMT) MODEL

This chapter presents the pre-existing monitoring and treatment of colorectal cancer patients, from the medical evaluation appointments to the completion of chemotherapy sessions. In addition, the proposed new computational model of monitoring is presented.

4.1 Pre-existing Monitoring and Treatment

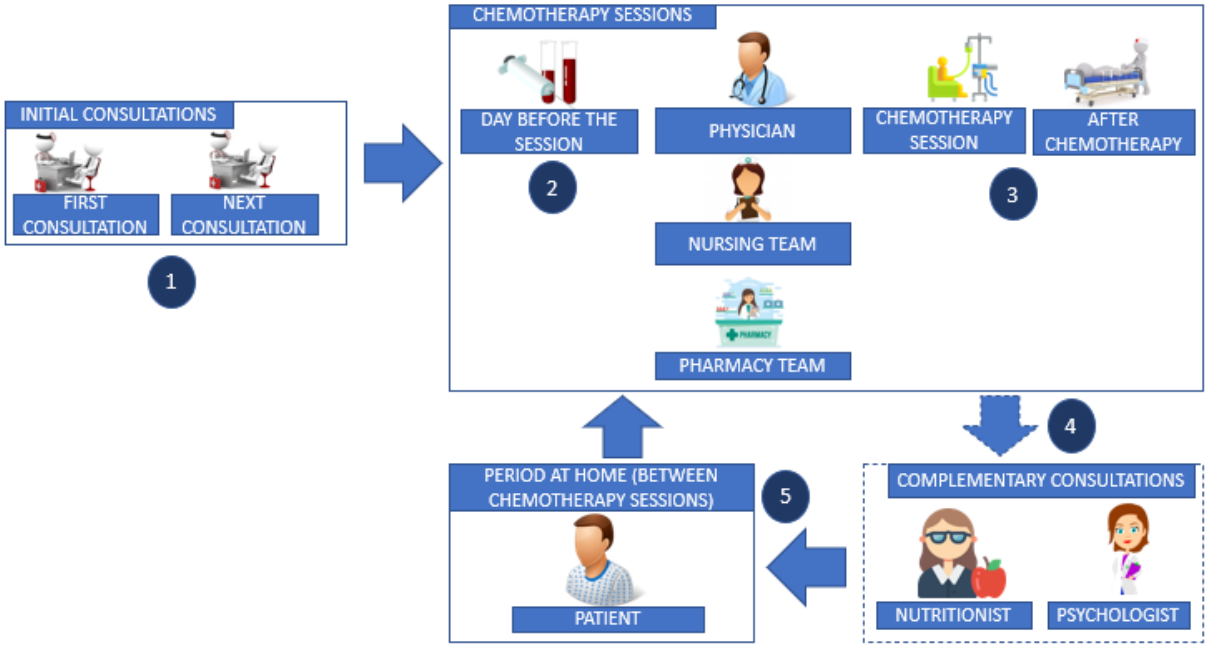
Figure 8 shows an overview of the pre-existing monitoring and treatment. The 1st stage refers to the medical evaluation appointment where the doctor evaluates the patient and requests the necessary tests to define the prognosis and the treatment to be carried out. Once the patient's cancer diagnosis is confirmed, the doctor clarifies the importance of carrying out the treatment and guides on the signs and symptoms of the disease and the adverse effects resulting from the treatment. In addition, the patient is instructed on the practice of physical activity. The physician presents the Informed Consent Form to the patient, and both sign it if the patient agrees to undergo the proposed treatment.

The 2nd stage refers to the exams patients perform the day before the chemotherapy session. The 3rd stage refers to the conduct performed on the day of the chemotherapy session. At this stage, the Nursing team evaluates the exams, guides, clarifies doubts and asks patients if they have any signs, symptoms, and adverse effects. In addition, some indicators are measured: oxygen saturation level, heart rate, blood pressure, temperature, body weight, and height of the patient. If the Nursing team identifies any changes that could negatively impact the procedure, chemotherapy can be temporarily suspended or rescheduled until the patient is stabilized. Medications are then prepared by the pharmacist and applied to the patient. After chemotherapy, the Nursing team verifies the clinical data, and the patient waits for the stabilization of his clinical condition to be discharged.

The 4th stage refers to appointments with a nutritionist and psychologist. All patients in the 1st chemotherapy session are instructed to schedule appointments with these professionals; if they agree, the appointment is already scheduled. The patient receives a personalized nutritional plan and psychological guidance in these appointments. Finally, the 5th stage refers to the period between chemotherapy sessions. During this period, patients must follow the guidelines of the multidisciplinary team, and, in case of an emergency, they must seek the nearest emergency room for medical evaluation and inform the doctor as soon as possible.

However, during this period, no control is focused on monitoring whether the patient follows the treatment as instructed.

Figure 8: Overview of the pre-existing monitoring and treatment: 1) period of medical evaluation appointments until the prognosis is defined; 2) completion of mandatory exams for each chemotherapy session; 3) professionals who interact with the patient on the day of the chemotherapy session: physician; pharmacist and nurse; 4) complementary appointments that are suggested to the patient diagnosed with cancer; 5) period between chemotherapy sessions, in this period the patient performs the self-management of medications and care, according to the medical recommendation.



4.2 Proposed Computational Model of Monitoring

Our proposed model focuses mainly on when the patient is at home (between chemotherapy sessions), represented in Figure 8, in the 5th stage. Figure 9 presents the proposed computational monitoring model, called Smart Monitoring Tool. We encourage the patients to be better involved in their treatment, improve self-management, and report their clinical condition. The proposed computational model involves the use of AI and IoT techniques. The patient interacts with the chatbot passively or actively. Based on the interactions, the patient receives feedback, and the multidisciplinary team can be notified if the deterioration of the patient's clinical condition is identified. Physical activity data are collected through wearable devices and integrated into the chatbot. The data described in APPENDIX 1 - DEMOGRAPHIC AND CLINICAL DATA are extracted from the patient's medical records. The data reported by the patient are stored in a centralized database. Only authorized users have access to the data. Access to the chatbot is available through the Facebook Messenger app and Facebook page, accessed through the notebook, smartphone, and tablet.

Figure 9: Architecture of the proposed model.

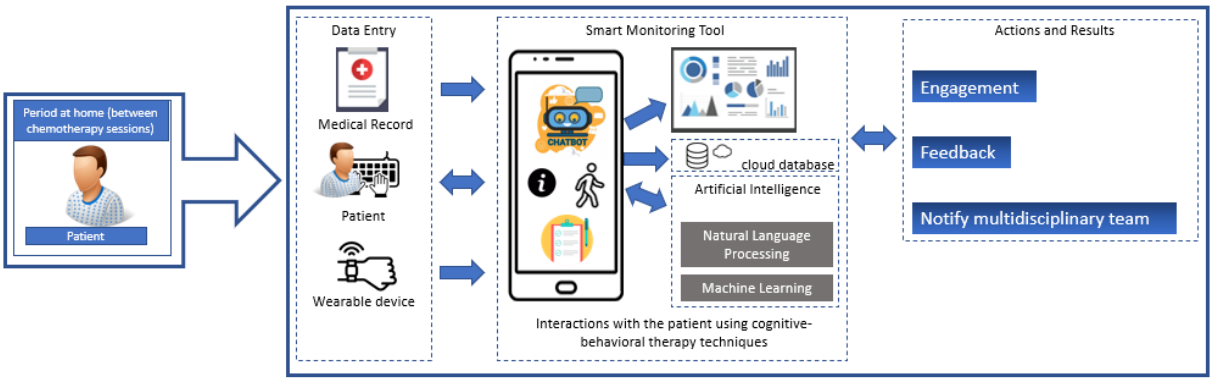


Figure 10 shows how the patient interacts with the chatbot. The patient starts by choosing one of the available options, Symptoms / Adverse Effects, Physical Activity, Food, and Questionnaire. If the patient decides on symptoms/side effects, the patient must choose one of the related symptoms or type what he is feeling. Thus, the chatbot interacts with the patient according to the reported data. At the end of the flow, the chatbot can recommend the patient to continue following the medical recommendation, schedule an appointment with your doctor as soon as possible, or seek the emergency room as quickly as possible. Depending on the deterioration of the clinical condition, the multidisciplinary team is notified.

If the patient chooses physical activity, the walking distance and the number of steps must be informed. If the patient has not performed physical activity, the patient must report the reason for not completing it. If the patient chooses food, then the patient must inform whether he is eating less, equal, or more concerning what he ate before starting the treatment. In addition, the system asks patients to describe their opinion about the menu proposed by the nutritionist for each type of meal, breakfast, lunch, snack/coffee break, and dinner. When choosing the questionnaire option, the patient must answer the Quality of Life of Cancer Patients or the Colorectal Surveys.

Figure 11 presents how the chatbot interacts with the patient. The chatbot starts the flow by reminding or notifying the patient about a specific topic. Regarding symptoms/adverse effects, the model asks the patient about the most critical symptoms, such as pain and fever. Regarding physical activity, the model reminds the patient about the importance of physical activity for the treatment and guides the patient to exercise if he still needs to do it according to the medical recommendation. Food is verified if the patient eats well and follows the nutritionist's advice. Finally, if the patient has yet to respond to the questionnaires as planned, the model notifies the patient to respond as soon as possible. Subsequently, after interacting with the chatbot, the patient receives personalized guidance and feedback according to the reported data.

Figure 10: The patient starts interacting with the chatbot with a greeting message, then the chatbot asks what the patient wants to talk about, and, finally, the patient chooses one of the options. After interacting on the chosen subject, the model provides feedback and guidelines to the users, such as continuing to follow the medical recommendation and contact the chatbot again if symptoms persist; schedule a medical appointment; seek emergency care as soon as possible.

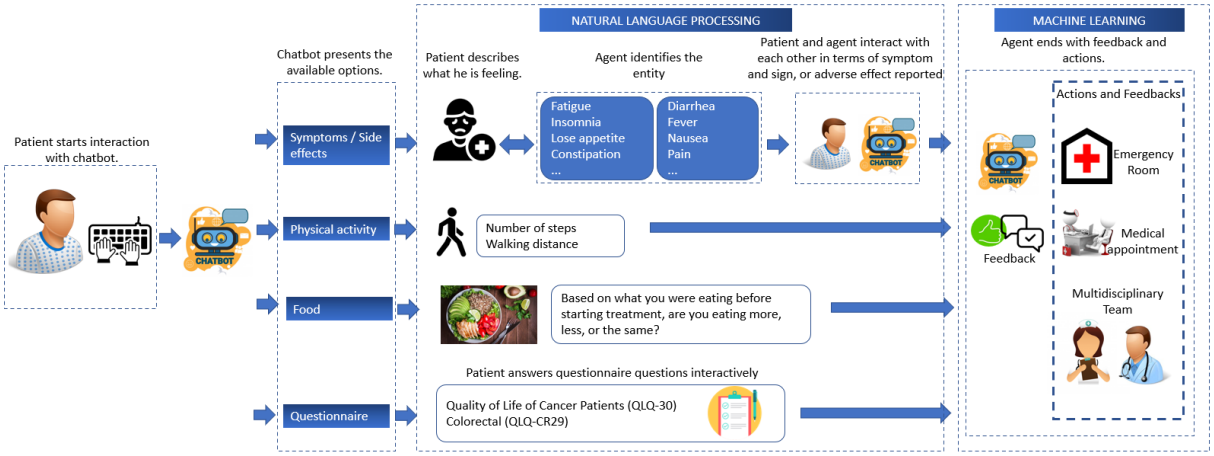


Figure 11: The chatbot starts interacting with the patient by reminding or notifying the patient about a specific topic. The patient interacts with the chatbot about the topic, and, finally, the patient receives guidance and/or personalized feedback according to the reported data.

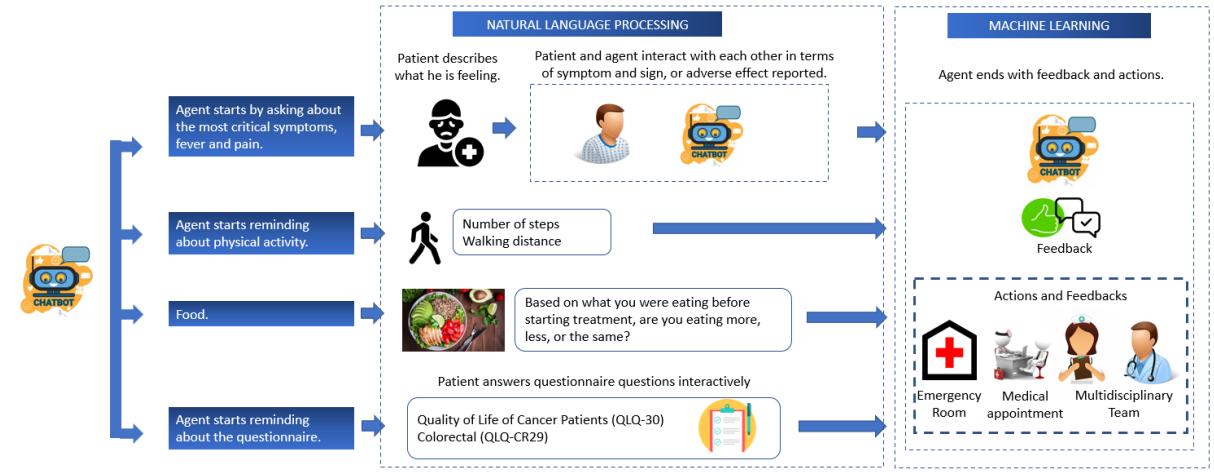
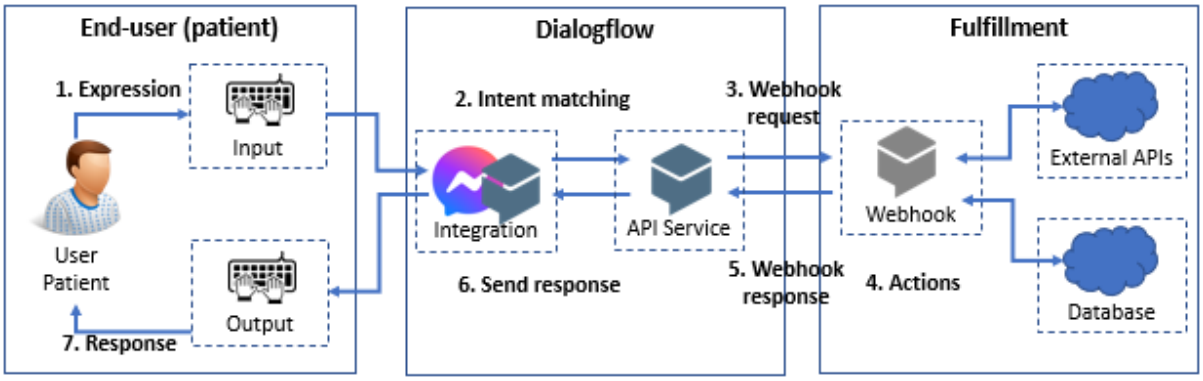


Figure 12 presents the model architecture design. It comprises Natural Language Processing (NLP) and Natural Language Understanding (NLU) to recognize user requests and return responses. NLP facilitates reading, understanding, decoding, and make sensing of human languages (BHARTI et al., 2020). Users make requests through the integration system platform (Facebook Messenger). Dialogflow takes the user's natural language information and processes it to select the matching intent that fulfills the user's request (GOOGLE, 2022). Depending on the activated intent, Dialogflow returns the system response defined in that intent to the user (BHARTI et al., 2020; GRIOL et al., 2022; MACHIDON et al., 2020). If the selected intent needs to perform some additional operation, a request is sent to the webhook to respond to the user. The webhook is performed through integrations with Google Cloud Functions and

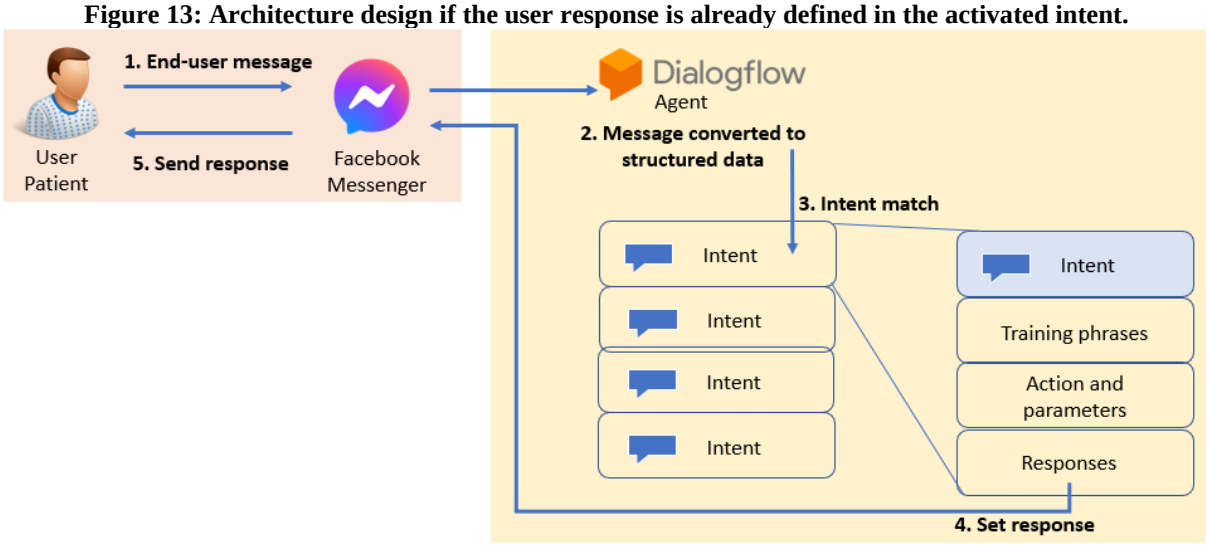
Firebase database to perform those operations (GRIOL et al., 2022). Finally, after processing, the webhook responds to the message to Dialogflow, which processes it to send it to the user in an appropriate format (BHARTI et al., 2020; GRIOL et al., 2022; MACHIDON et al., 2020). In addition, depending on the activated intent, the system stores the user request and webhook response information in the database so that they can be accessed later if necessary (BHARTI et al., 2020; GRIOL et al., 2022; MACHIDON et al., 2020).

Figure 12: Model architecture design.



Dialogflow comprises an agent, intents, and entities, among others. Dialogflow agent is a virtual agent with the skills to handle simultaneous conversations with your end-users (GOOGLE, 2022). Based on the user's text or voice message, Dialogflow converts the message into structured data so your apps and services can understand (GOOGLE, 2022). Based on this data, Dialogflow matches the end-user message with the best intent within the agent. Finally, the end-user receives the response and can interact with the agent (GOOGLE, 2022). Figure 13 presents the architecture design if the user response is already defined in the activated intent.

Figure 13: Architecture design if the user response is already defined in the activated intent.



4.3 Recommender System

The recommendation system aims to automate patient feedback and guidance during treatment. The proposed system is based on content-based and collaborative filtering techniques. The patient's chemotherapy protocol and evaluations of recommendations made by patients with similar protocols are the basis for defining new recommendations for patients.

Figure 14 presents the model architecture, including the recommender system. This model proposes more assertive and precise recommendations for each symptom and adverse effect patients reported. The content-based technique affords recommending guidelines well evaluated by patients with the same protocol. Furthermore, the use of a technique based on collaborative filtering allows for recommending guidelines well evaluated by other similar patients.

The basis for building the recommender system to address patients' expectations is mapping the main symptoms and adverse effects reported by patients with colorectal cancer in the active phase of treatment (Figure 15). Their mapping was based on interviews with the nursing team at Cecans, extracted from the Pharmaceutical Guide of Hospital Sírio-Libanês (HOSPITAL SIRIO-LIBANÊS, 2023), and on data collected during the application of the model proposed in this thesis.

Thus, for each adverse effect and symptom reported, it is essential to define the most common guidelines given to patients with colorectal cancer undergoing chemotherapy. Table 9 presents examples of personalized guidelines. In peripheral neuropathy, for example, some recommendations were defined that should be sent to the patient in the first cycle of chemotherapy according to the prescribed protocol. In addition, recommendations were determined to minimize this adverse effect of treatment. These options can be used individually or combined with each other by the recommender system engine.

Figure 14: Model architecture including the recommender system.

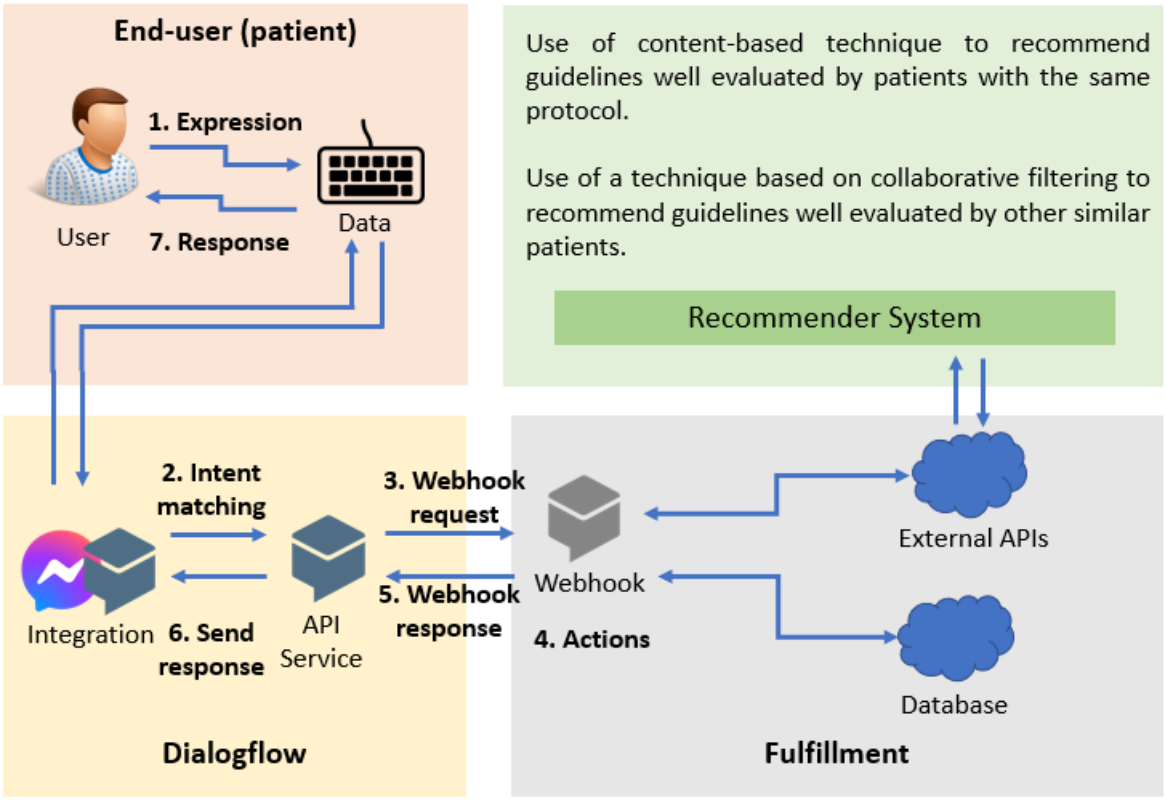


Figure 15: Main symptoms and adverse effects reported by patients with colorectal cancer in the active phase of treatment.

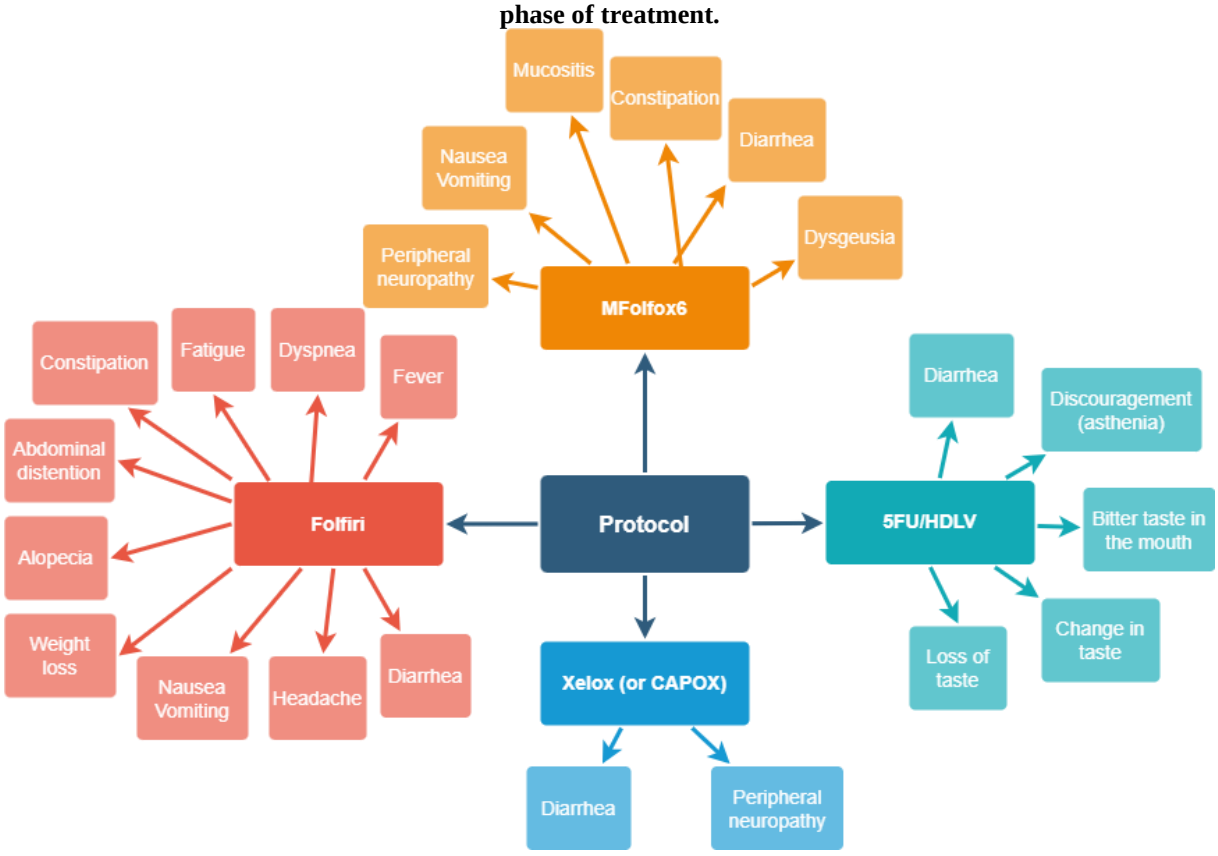


Table 9: Main symptoms and adverse effects related to chemotherapy treatment in colorectal cancer patients.

ID	Symptoms/ Adverse Effects	ID	Recommendations
1	Peripheral neuropathy	1.1	Recommendation of the first chemotherapy session in protocols mFolfox6 and Xelox (or CAPOX): • Avoid places with air conditioning (bedrooms, living rooms, among others). When sleeping, bundle up and/or cover up. • Avoid contact with places, objects, and surfaces with ice. Avoid touching the fridge, get ice. Avoid taking things out of the fridge. If necessary, make contact, preferably, with gloves or some type of protection to avoid direct contact. • Tingling or numbness in the hands, feet, legs, and arms, as well as in other parts such as the mouth and ears; weakening or loss of any of the senses, especially touch; and decreased sensitivity, and cramps. These symptoms may be precipitated or exacerbated by exposure to cold temperatures or objects (HOSPITAL SIRIO-LIBANÊS, 2023).
		1.2	More recommendations: • Option 1: o Have a fabric glove in the kitchen (usually in the place where you have more contact with cold surfaces or objects), and avoid going barefoot (try to always wear tighter socks or shoes), especially when you feel more sensitive.
		1.3	• Option 2: o Avoid exposure to cold and ingestion of cold foods and drinks during or in the hours following drug administration (chemotherapy) (HOSPITAL SIRIO-LIBANÊS, 2023). o Try to drink plain water. Slightly warm the water before drinking. Slightly warm the food.
		1.4	• Option 3: o During this protocol, it is recommended to avoid contact with cold surfaces/objects/food/environments even when you are not feeling very sensitive so that this adverse effect can be mitigated or postponed. The more tactful you are, the more stimulus sensitivity can be generated.
		1.5	• Tingling: o To reduce tingling, the recommendation is to practice physical activity. Need to walk even with the tingling. It is necessary to walk to stimulate circulation for the adverse effect to improve. The suggestion is to walk around the court at home, indoors, or take a light walk around your home. It is important to stimulate your body's circulation.
		1.6	The patient reports intense difficulty holding objects or walking due to tingling and numbness in the hands and/or feet: • The recommendation is to contact your doctor as soon as possible or to seek an emergency room.
2	Nausea/vomiting	2.1	• It is recommended to consume foods that are slightly drier and slightly more acidic, which can help reduce salivation and reduce the bitter taste in the mouth. It is usually this feeling of dry mouth and bitter taste in the mouth that contributes to nausea.
		2.2	• Examples of slightly more acidic foods: pineapple, kiwi, lemon juice, and Gatorade.

			○ In its protocol, it is not recommended to consume cold foods due to the sensitivity that can be generated by the medication. ○ In the Mfolfox6 and Xelox protocols, cold fruits, drinks, and foods are not suitable due to the sensitivity that the medication can also cause in the throat.
		2.3	• It is recommended not to spend a long time without eating, try to eat in a shorter time interval between meals.
3	Bitter taste in the mouth	3.1	• It is recommended to consume more acidic foods (examples: pineapple, kiwi, and lemon juice), ginger candies, mint candies, and sucking ice cubes.
		3.2	• It is recommended to always have something to chew on (for example: nuts, seeds, fruits, cookies). Always eat something so you don't get the constant bitter taste in your mouth.
4	Mucositis	4.1	• It is recommended to rinse with a solution prepared from 250 ml of water and a teaspoon of dissolved sodium bicarbonate. You should not swallow the prepared solution, it should only be used for rinsing. ○ If you don't have bicarbonate, you can use a vitamin E ampoule that has the consistency of a gel. Break the ampoule and apply the gel directly to the sores and canker sores in the mouth and cheeks.
		4.2	• It is recommended to use the Hexomedine spray, following your doctor's instructions, which you can spray in your mouth for an anesthetic effect to relieve discomfort.
		4.3	• It is recommended to use Flogoral in tablet form or syrup, following your doctor's instructions.
5	Constipation	5.1	• Option 1: ○ It is recommended to (diet tip) increase fiber intake to 20-35 grams/day and fluids (at least 1.5-2 liters a day). ○ It is recommended to consume foods and fruits rich in fiber to normalize intestinal function, such as papaya, beetroot, okra, fresh or dried plums, apples, pears, and unpeeled peaches.
		5.2	• Option 2: ○ It is recommended to drink a lot of water, a lot of fluids in general (at least 1.5-2 liters a day). ○ Regular consumption of fiber is indicated, such as oatmeal, oat flakes, and fiber-rich fruits (for example: papaya, beetroot, okra, fresh or dried plums, apples, pears, and unpeeled peaches).
		5.3	• It is recommended to use Tamarine in syrup, capsule, or jelly, following your doctor's instructions. It is a natural product and is usually found in pharmacies or health food stores.
		5.4	• It is recommended to consume a portion (teaspoon) of coconut oil. It can be purchased in markets or natural products stores.
		5.5	• Here are some behavioral guidelines: ○ Discipline the appearance of the reflex with the condition of doing it every day, that is, whenever you have a chance to poop, do it, preferably, at the same time every day. Reflex conditioning is present after 2-3 weeks of training. ○ Dedicate all your attention, without distractions. ○ Adopt a sitting posture, with the support of the lower limbs on the floor, working as a lever, and flexing the trunk over the abdomen, avoiding the reclining attitude.

			○ Increased physical activity is accompanied by greater regularity of defecation, that is, physical activity helps you to poop (evacuate) more regularly.
6	Diarrhea	6.1	• Recommendation of the first chemotherapy session in protocol Folfiri: ○ The recommendation is to drink a lot of fluids (water, sports drinks, among others). ○ It is recommended to use loperamide in the first 48 hours after the onset of diarrhea, following your doctor's instructions (HOSPITAL SIRIO-LIBANÊS, 2023). If even taking loperamide the diarrhea does not stop, the advice is to seek an emergency room.
		6.2	• Option 1: ○ The recommendation is to drink a lot of fluids (water, sports drinks, among others).
		6.3	• Option 2: ○ It is recommended to hydrate with homemade serum, isotonic (for example: Gatorade) and flavored water. If you have nausea/vomiting, choose to consume the most palatable drink for the moment. ▪ Instructions for preparing homemade serum: in 1 liter of mineral water, filtered or boiled (but already cold), mix 1 tablespoon of sugar (20 g) and 1 teaspoon of salt (3.5 g).
		6.4	• It is recommended to use loperamide in the first 48 hours after the onset of diarrhea, following your doctor's instructions (HOSPITAL SIRIO-LIBANÊS, 2023). If even taking loperamide the diarrhea does not stop, the advice is to seek an emergency room.
		6.5	• In addition to symptoms, the patient reports blood or mucus in diarrhea: ○ The recommendation is to contact your doctor as soon as possible or to seek an emergency room.
7	Alopecia (Hair loss)	7.1	• Option 1: ○ Hair loss during cancer treatment is expected. I know it's hard, but it's part of the therapeutic moment you're in right now. ▪ It is recommended to avoid washing your hair several times a week. Give preference to wash 1 to 2 times a week. ▪ Avoid combing/brushing your hair several times a day. ▪ Cut your hair if you feel more comfortable when you notice hair loss. ▪ Wear a wig and scarf if you feel more comfortable.
		7.2	• Option 2: ○ It is recommended not to wash your hair every day. Avoid washing your hair too often. Avoid brushing your hair several times a day. Some attitudes will help ease the period of hair loss, but there is no way to prevent hair loss.
		7.3	• Option 3: ○ Unfortunately, it is not possible to stop hair loss, however, to reduce hair loss, it is recommended to avoid washing your hair too often and use a brush moderately. If you feel more comfortable, you can cut your hair a little or adopt a scarf.
8		8.1	• Option 1:

	Discouragement, asthenia, fatigue		○ It is recommended to practice physical activity, for example, walking, at least 3 times a week for a period of 20 to 30 minutes, which can help you to improve fatigue (weakness). Physical activity should be light and of low impact during the treatment period.
		8.2	• Option 2: ○ It is recommended to practice a hobby or an activity that gives you pleasure, for example, walking, taking a walk in the park, listening to music, reading a book, watching a movie, going out with family, and meeting friends. Seek to perform an activity that gives you satisfaction.
		8.3	• In addition to the symptoms, the patient reports swelling and coughing: ○ The recommendation is to schedule an appointment with your oncologist as soon as possible.
		8.4	• In addition to the symptoms, the patient reports chest pain, loss of consciousness/fainting, and/or changes in the face/speech: ○ The recommendation is to contact your doctor as soon as possible or to seek an emergency room.
9	Headache	9.1	• It is recommended to use dipyrone, following your doctor's instructions, and rest.
10	Abdominal distension	10.1	• Unfortunately, due to medication, the patient has a swollen abdomen. In case of doubt, it is recommended to consult your doctor.
11	Change in sense of smell (smell becomes more acute)	11.1	• It is recommended to avoid places and exposure to environments that cause this stimulus. Avoid being in the kitchen with people cooking.
12	Fever	12.1	• Temperature above 38º ○ Stay tuned! If you have a fever above 38° for a period longer than 1 hour or after taking the medication you have a fever equal to or greater than 38.3°, the recommendation is to contact your doctor as soon as possible or to seek an emergency room.
		12.2	• Temperature between 37º and 37.9º ○ There is currently no need to worry. The recommendation is to shower with slightly cold water and continue taking the medications indicated by the doctor.
		12.3	• Temperature below 37°: ○ Do not worry. Your temperature is normal. The recommendation is to relax and continue doing your activities normally.
13	Pain	13.1	• The patient reports mild or moderate pain (level up to 2 on a scale up to 5) ○ The recommendation is to continue taking the medications as recommended by the doctor (continue monitoring). If you are unable to take your pain medication, it is recommended that you contact your doctor as soon as possible.
		13.2	• Patient reports moderate pain (level 3 on a scale up to 5) ○ The recommendation is to schedule an appointment with your oncologist as soon as possible. In addition, you must continue taking the medications as recommended by the doctor.
		13.3	• Patient reports severe pain (level above 3 on a scale up to 5) ○ The recommendation is to contact your doctor as soon as possible or to seek an emergency room.

14	Insomnia	14.1	• Here are some important tips that can help you get a good night's sleep: o Get up every day at the same time and maintain a sleep routine; o Limit the amount of time lying in bed before sleep; o Limit or suspend psychotropic substances (alcohol, caffeine, stimulants, among others); o Avoid sleeping during the day; o Physical activity: perform in the morning and avoid practicing for about four hours before bedtime; o Avoid stimulating activities at night: TV, cell phone, and social networks; o Avoid heavy evening meals; o Keep a room suitable for sleep: reduce stimuli such as light and sound; o Avoid screens before or at bedtime (computers, phones, tablets, e-books); o Solve problems before bedtime; o Do not force sleep; o Meditate or perform relaxation techniques.
15	Weight loss	15.1	• It is recommended to observe how your diet is and if you are eating enough protein. Try to reinforce your diet, eat more times a day, and try to eat foods that provide sustenance. Thus, the guidelines are to increase the percentage of protein and eat more times a day. Sometimes you won't be able to eat anymore because you're feeling nauseous, but it's important to try it.
16	Lose appetite	16.1	• Option 1: o It is recommended to prioritize the consumption of food more frequently during the day and in small quantities. It is indicated to consume what you like and give you pleasure, the important thing is to eat.
		16.2	• Option 2: o It is recommended to eat small portions every 2 hours. This will help you to be able to eat better.
		16.3	• Usually, during this period, the consumption of lighter, pastier, and more liquid and easy to swallow foods, such as soups and broths, is indicated, however, consume what best pleases your palate.
17	Excessive food consumption	17.1	• It is recommended that you continue eating normally. Give preference to healthy foods, fruits, vegetables, and protein sources such as meat, chicken, cheese, and eggs. The important thing for the treatment at this point is that you can feed yourself. This is crucial for your recovery. However, try to control the amount of food ingested, and avoid excess.
18	Food	18.1	• In general: o Option 1: ▪ During treatment, you can eat normally. This is vital for your recovery. Give preference to healthy foods, fruits, vegetables, and protein sources such as meat, chicken, cheese, and eggs. ▪ Avoid hurting the mouth, prioritize easy-to-swallow foods such as soup, gelatin, broth, ice cream, and yogurt. ▪ Avoid solid foods like crunchy, dry, and hard foods. Avoid very acidic foods. Avoid processed foods in

		general, especially those that contain artificial colors and preservatives.
18.2	• In general: o Option 2: ▪	There is no restriction on food, it is allowed to eat all types of meat, eggs, grains, vegetables, and legumes. Special attention should be paid to meat, beans, and salads (the greener the better), as they are foods rich in nutrients needed for the treatment to proceed smoothly.
18.3	• In general: o Option 3: ▪	Avoid raw foods, except for salads, but these will also need to be washed properly. Prepare a solution, with two tablespoons (soup) of vinegar to 1 liter of filtered water. After that, let the vegetables and fruits soak in this mixture for approximately 30 minutes. After this time, just rinse it in running water and dry it in the salad dryer.

5 METHODOLOGY

The methodology of the present study is divided into four stages. The first stage includes developing the Smart Monitoring Tool (SMT) software, and the second includes carrying out a pilot study to evaluate the SMT. The third consists of a prospective non-randomized clinical study. Participants in the pilot study were the multidisciplinary team of Cecans (Sinop Cancer Center), and the prospective study was colorectal cancer patients treated by Cecans. Finally, the fourth stage includes a case study to evaluate SMT integrated with the recommender system (Figure 16).

Figure 16: Stages of the proposed methodology for the construction and evaluation of the SMT model.

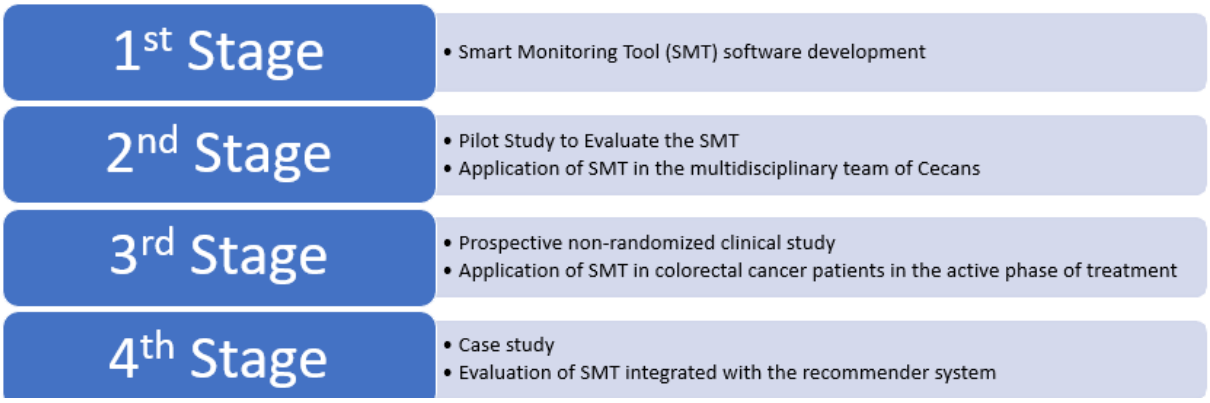
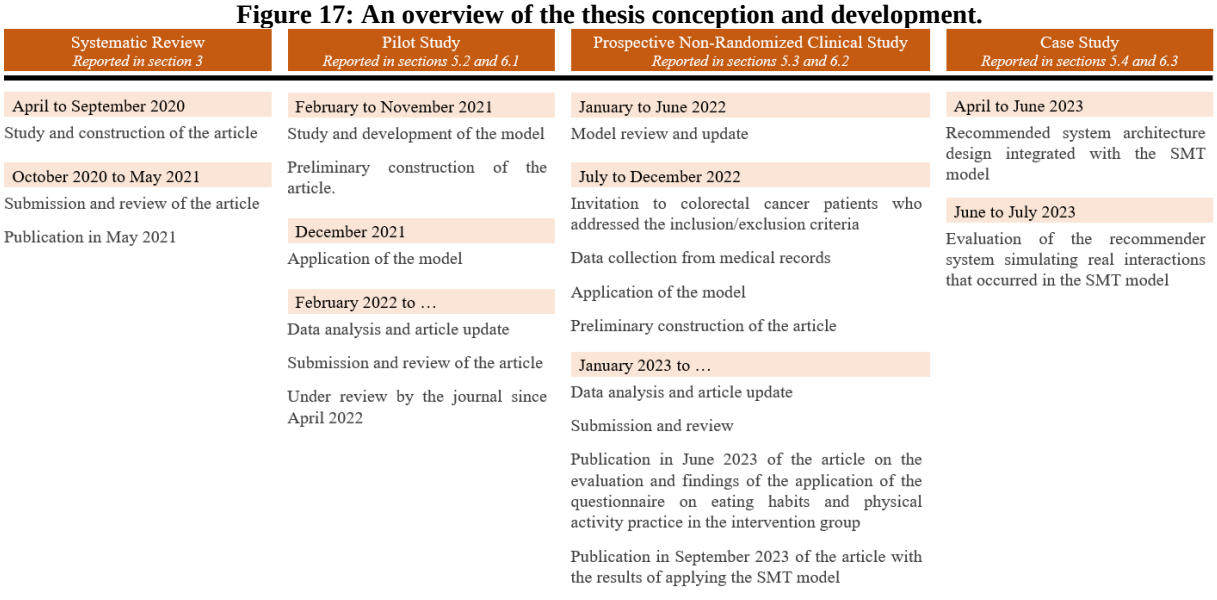


Figure 17 presents an overview of the thesis conception and development. The systematic review was the first work carried out (reported in section 3 of this thesis), and later, we developed the model and its application in the scope of a pilot study (reported in sections 5.2 and 6.1). The third was a prospective non-randomized clinical study (reported in sections 5.3 and 6.2), and finally, we performed a case study (reported in sections 5.4 and 6.3).

Figure 17: An overview of the thesis conception and development.



5.1 Smart Monitoring Tool (SMT) Model Development

Figure 18 presents the components of the model. The model is composed of information on cancer-related signs and symptoms, information on treatment-related adverse effects, surveys, a chatbot, and a wearable device for physical activity data collection. The concepts of each module of the SMT model are described below:

- **Information on signs and symptoms of cancer:** Based on the literature, a list of the most common signs and symptoms resulting from the disease is available. In addition, the solution contains activities indicated to patients to alleviate or prevent it.
- **Information on adverse effects related to cancer treatment:** Based on the literature, a list of the main adverse effects that can be caused by cancer treatment is available. Suggestions of activities for the participant to carry out to mitigate such adverse effects are also available.
- **Physical activity:** The participant must record the number of steps and walking distance measured by the wearable device in each physical activity performed according to medical advice.
- **Surveys:** During cancer treatment, the participants must answer the questionnaires through the chatbot. The project includes two questionnaires developed by the European Organization for Research and Treatment of Cancer (EORTC).
    1. Quality of Life of Cancer Patients (QLQ-C30): addresses questions about the general health of a cancer patient.
    2. Colorectal (QLQ-CR29): addresses experiences with symptoms and problems that CRC patients face during treatment.
- **Chatbot:** The chatbot interacts with patients about signs, symptoms, or adverse effects and the perceived intensity. According to the reported intensity, the patient receives feedback on the action to be taken, and the multidisciplinary team receives real-time notification of the clinical condition reported by the patient. We do not perform patient diagnoses; we only reinforce the guidelines that were given by the doctor. The application interacts with the patient through the chatbot based on the patient's report, as seen in Figure 19. In addition, the app can also stimulate the patient. For example, according to a pre-defined frequency, the application asks the patient if he feels or has felt any sign, symptom, or adverse effect. The questions are related to some specific symptoms

to help the patient remember. Based on the patient's response, the application indicates some action, as seen in Figure 20 and Figure 21. The chatbot also measures the level of engagement with the treatment based on interactions performed with the chat.

Figure 18: Application functionality *Smart Monitoring Tool*.

Figure 19: Patient interaction with the chatbot.

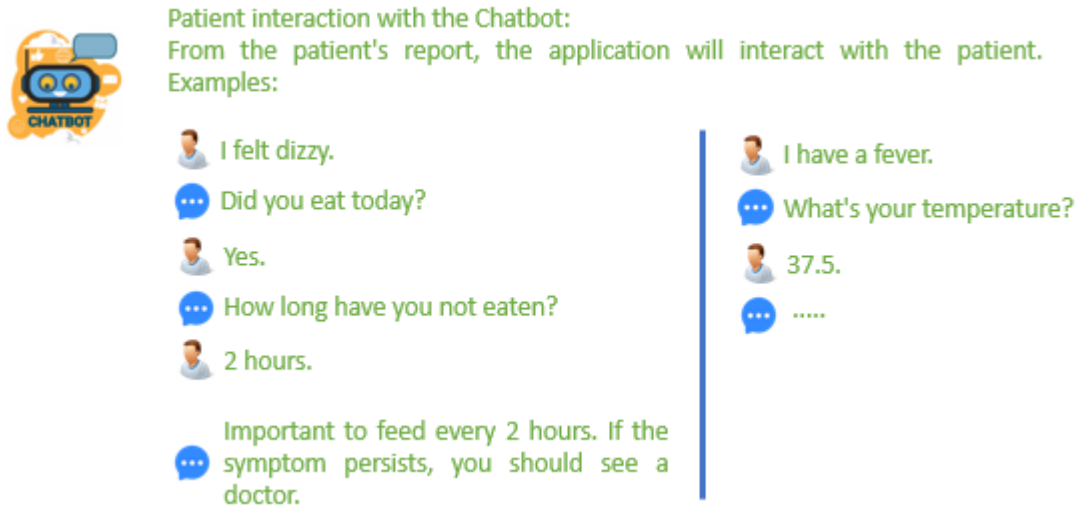
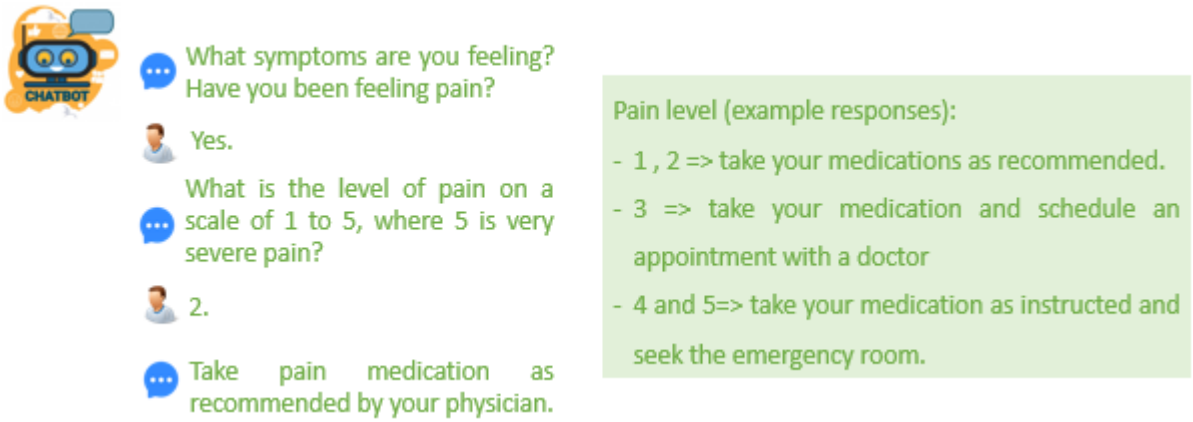


Figure 20: Patient being encouraged to interact with chatbot about one of the signs of illness. List of predicted responses given by the chatbot according to the pain level reported by the patient.



Twenty-one diagrams were developed to cover the signs, symptoms, and adverse effects. The diagrams contemplated specific flows for each level of criticality of data reported by the patient. The diagrams were built using diagrams.net, an open-source application. Figure

22 shows a partial example of the fever diagram. At the beginning of the interaction, the patient must choose one of the available options: Symptoms / Side effects, Physical activity, Food, and Questionnaire. In this example, the user chose Symptoms / Side effects. Now, the user must select one of the related symptoms or type what he is feeling. The Dialogflow agent processes the message and checks which intent matches. Finally, the chatbot displays a message to confirm that the symptom identified by Dialogflow is correct; if correct, the flow continues; otherwise, the patient is asked to describe his feelings again.

Figure 21: Patient being encouraged to interact with chatbot about one of the symptoms of the disease and physical activity.

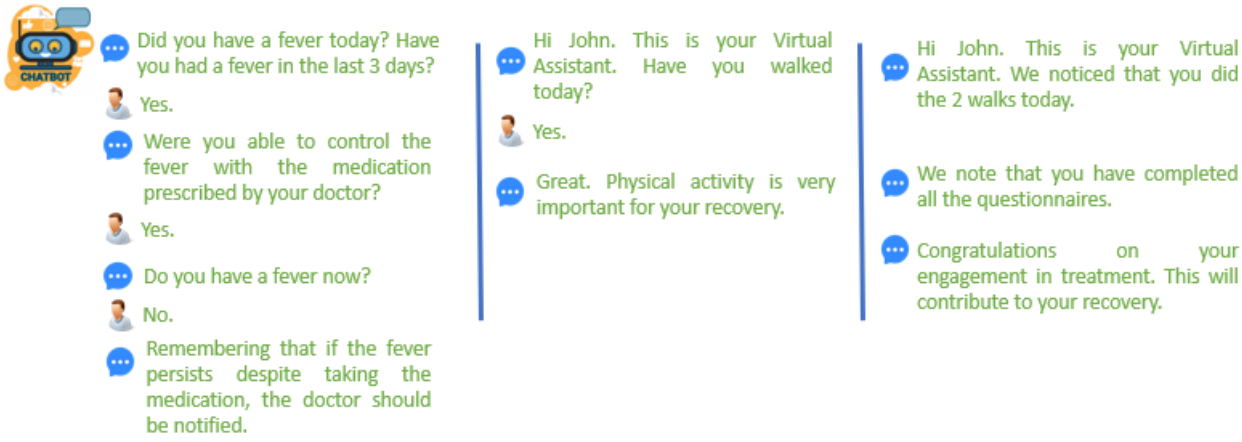


Figure 22: Example of diagram (fever) built in diagrams.net tool.

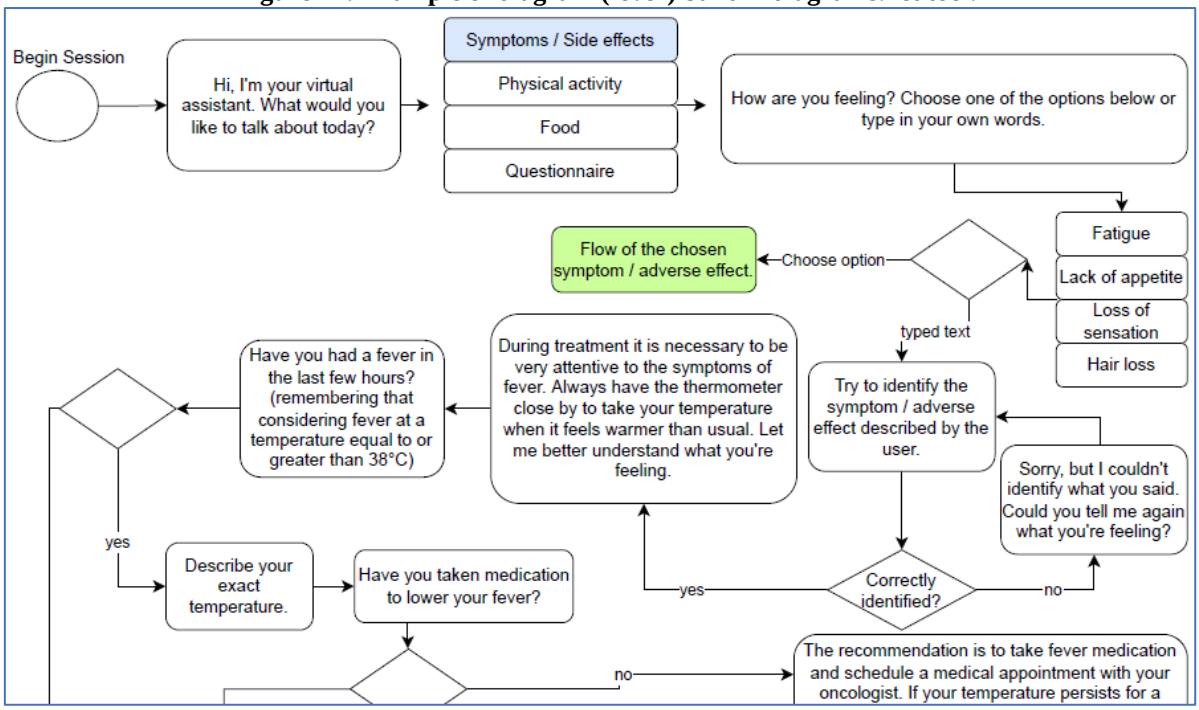


Figure 23 presents examples of patient-chatbot interactions and general feedback mapped to whether the patient reports any symptoms or adverse effects. At first, the patient describes what they are feeling, the chatbot identifies the symptom or adverse effect based on

the report, then starts the flow. Finally, the patient receives feedback according to the reported data. General feedback includes advising the patient to continue taking medications as recommended by the physician, schedule an appointment, or seek an emergency as soon as possible. All reports are shared in real-time with the clinic's healthcare team.

Figure 23: Overview of interactions between the patient and the chatbot.

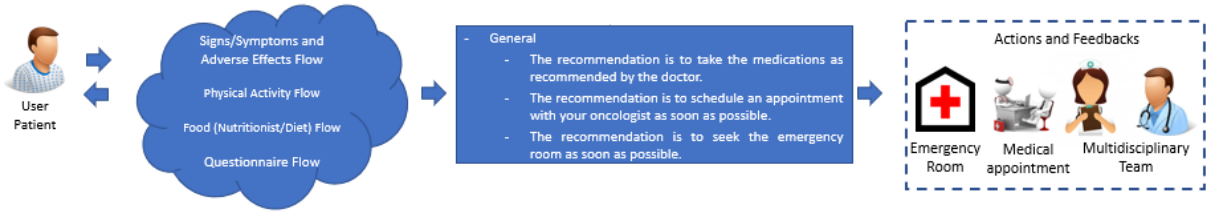


Figure 24 presents some proposed examples of specific feedback according to the clinical condition reported by the patient during interactions. Patients receive some guidelines to encourage the reduction of reported symptoms or adverse effects. For example, in case of diarrhea, the patient is instructed to drink plenty of fluids (water, sports drinks, among others). And in the case of constipation, the guideline is to increase fiber intake to 20-35 grams/day and fluids (at least 1.5-2 liters/day).

Figure 24: Examples of proposed feedback for each symptom and adverse effect.

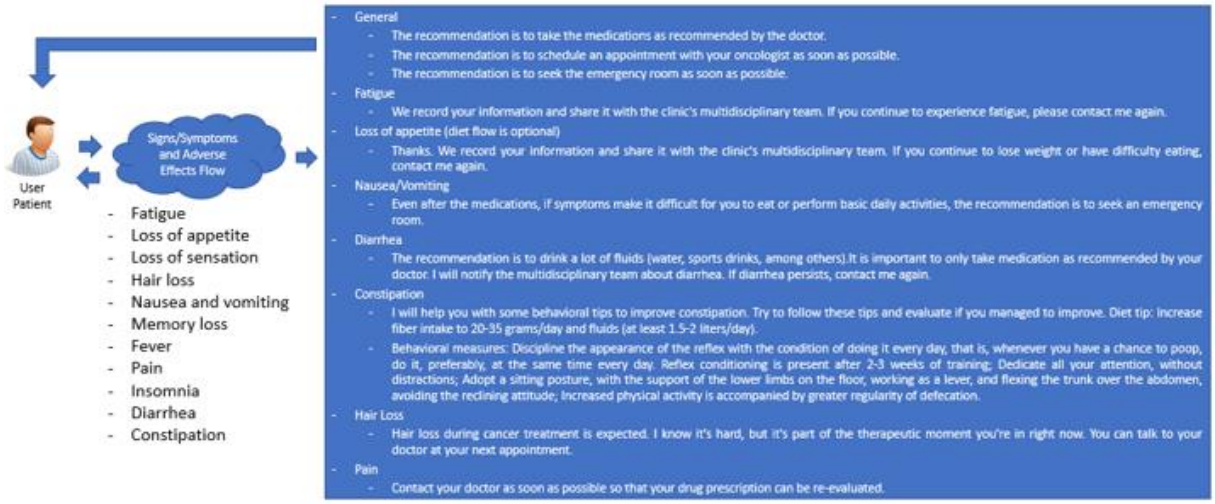
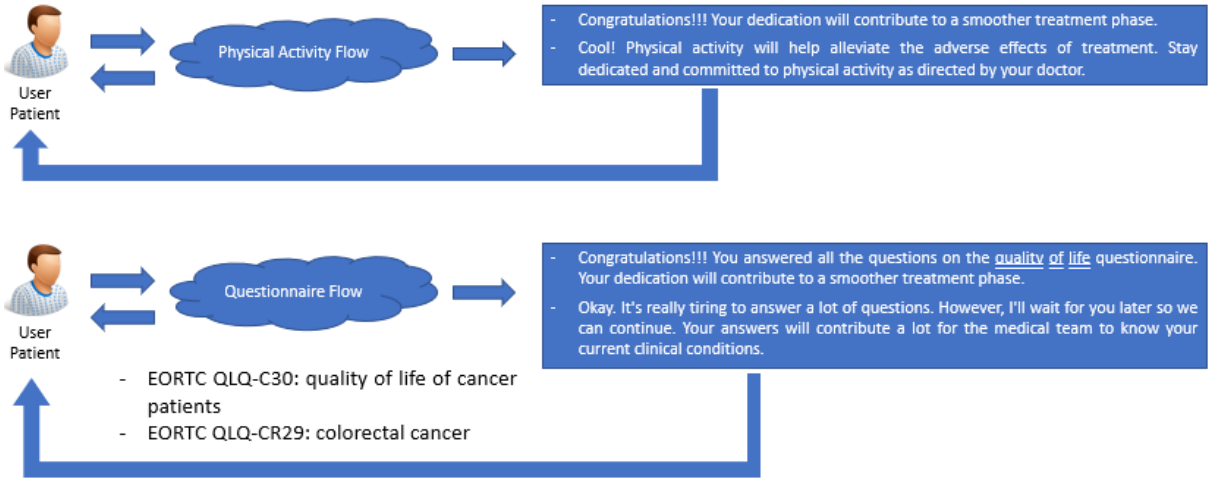


Figure 25 shows some defined feedback for when physical activity is reported to encourage patients to engage in physical activity. In addition, you can view proposed feedback when the user completes or interrupts the survey.

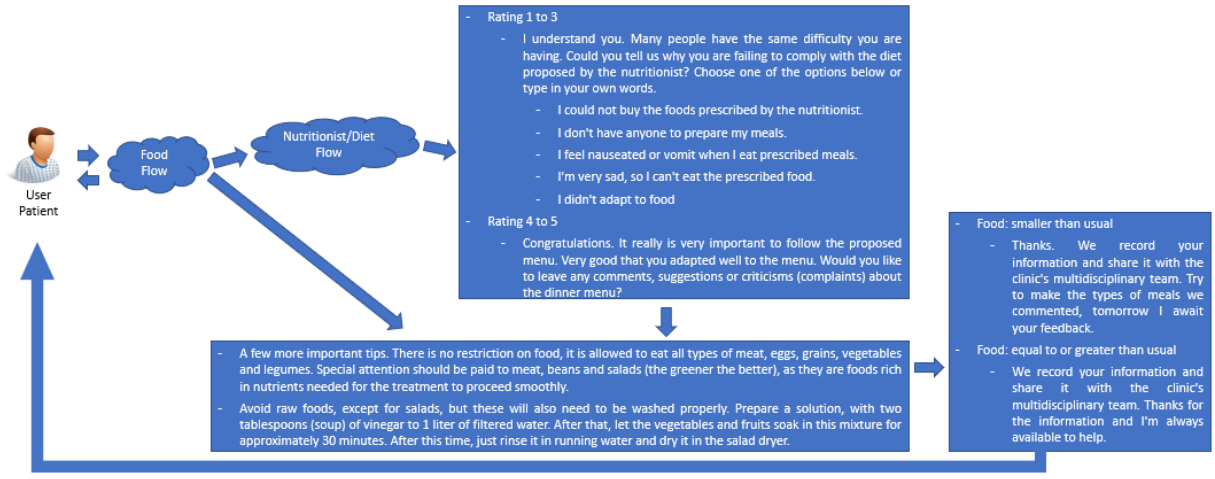
Figure 26 presents some feedback defined for the food flow. The nutritionist flow is optional in this flow, but it is recommended that the patient responds at least once every chemotherapy interval.

Figure 25: Examples of proposed feedback for physical activity and questionnaire flows.



The chatbot was developed using Google Dialogflow and integrated with Facebook Messenger. Dialogflow is a robust platform that combines Google's machine learning and natural language understanding capabilities and contributes to the design and integration of a conversational interface into web apps, bots, mobile apps, among others (KATAOKA et al., 2021), (HOLMES et al., 2019). Google Dialogflow has built-in integrations with common messaging platforms, such as Facebook Messenger, Telegram, Slack, and LINE, which allow developers to quickly integrate the chatbot with these platforms.

Figure 26: Examples of proposed feedback for the food flow.



5.2 Pilot Study to Evaluate the SMT

This section presents the methodology of the pilot study, whose objective is to evaluate the usability and user experience in the chatbot. It describes the type of study and the participants who participated, details how the intervention was carried out and the scope of the chatbot, and finally, highlights the tool used for data analysis. This pilot study was submitted

for evaluation in the Informatics for Health and Social Care in April 2022 and is currently under review status.

- QUEIROZ, D.A. de; COSTA, C.A. da; QUEIROZ, E.A.I.F. de; SILVEIRA, E.F. da; BETTONI, I.S.; MONTENEGRO, J.L.Z.; MOURA-FÉ, V.V. de. A Chatbot Application to Optimize Monitoring Colorectal Cancer Patients in the Active Treatment Phase. Informatics for Health and Social Care.

5.2.1 Study Type and Participants

A pilot study to assess the chatbot's usability, functionality, and user experience. The Cecans physicians participated in this study, along with paramedics, including pharmacists, nurses, nutritionists, psychologists, and employees working with CRC patients in the clinic or ward.

5.2.2 Intervention

All participants were invited to use the chatbot for one week. After this period, they answered the surveys on user experience (User Experience Questionnaire – UEQ) and usability (System Usability Scale – SUS). In this study, participants did not evaluate the usability and user experience of the wearable device. The complete model, including the wearable device, was assessed in the second evaluation stage, as described in section 5.3.

The UEQ assesses the user experience on six scales with 26 items in total: attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty (HOLMES et al., 2019), (COTA et al., 2014), (LAUGWITZ; HELD; SCHREPP, 2008), as shown in Figure 27. Scales are measured using pairs of opposite adjectives, where participants select the level of their perception. In addition, the UEQ scores contribute to assessing whether the system addressed the users' expectations (HOLMES et al., 2019), (TE PAS et al., 2020).

SUS is currently one of the most common surveys used to assess the usability of systems (HOLMES et al., 2019). SUS includes five questions about positive aspects and five questions about negative aspects to be applied during the evaluation, as shown in Figure 28 (HOLMES et al., 2019), (BANGOR; KORTUM; MILLER, 2008), (BROOKE, 1996). Users give the score on a scale from 1 to 5. The maximum score result is 100, being 68 considered the average score (HOLMES et al., 2019), (BANGOR; KORTUM; MILLER, 2008), (ISSOM et al., 2021). The SUS has a sufficient history of test scores, allowing its use as a basis of comparison to indicate

that a given interface is or is not sufficiently usable (BANGOR; KORTUM; MILLER, 2008). This survey provides a single score that estimates the overall usability of a product (BANGOR; KORTUM; MILLER, 2008). To the best of our knowledge, this is the first work that contemplates using a text-based chatbot focused on CRC patients undergoing active treatment.

Figure 27: Scale structure and items of the User Experience Questionnaire (UEQ).

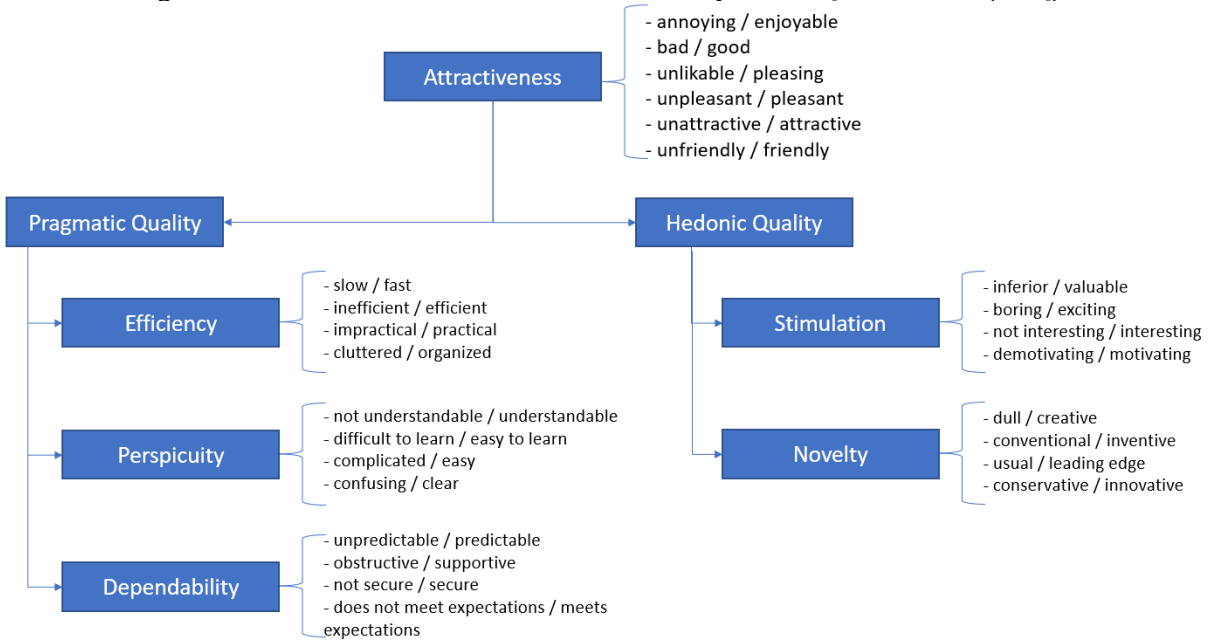


Figure 28: System Usability Scale (SUS) Questions.

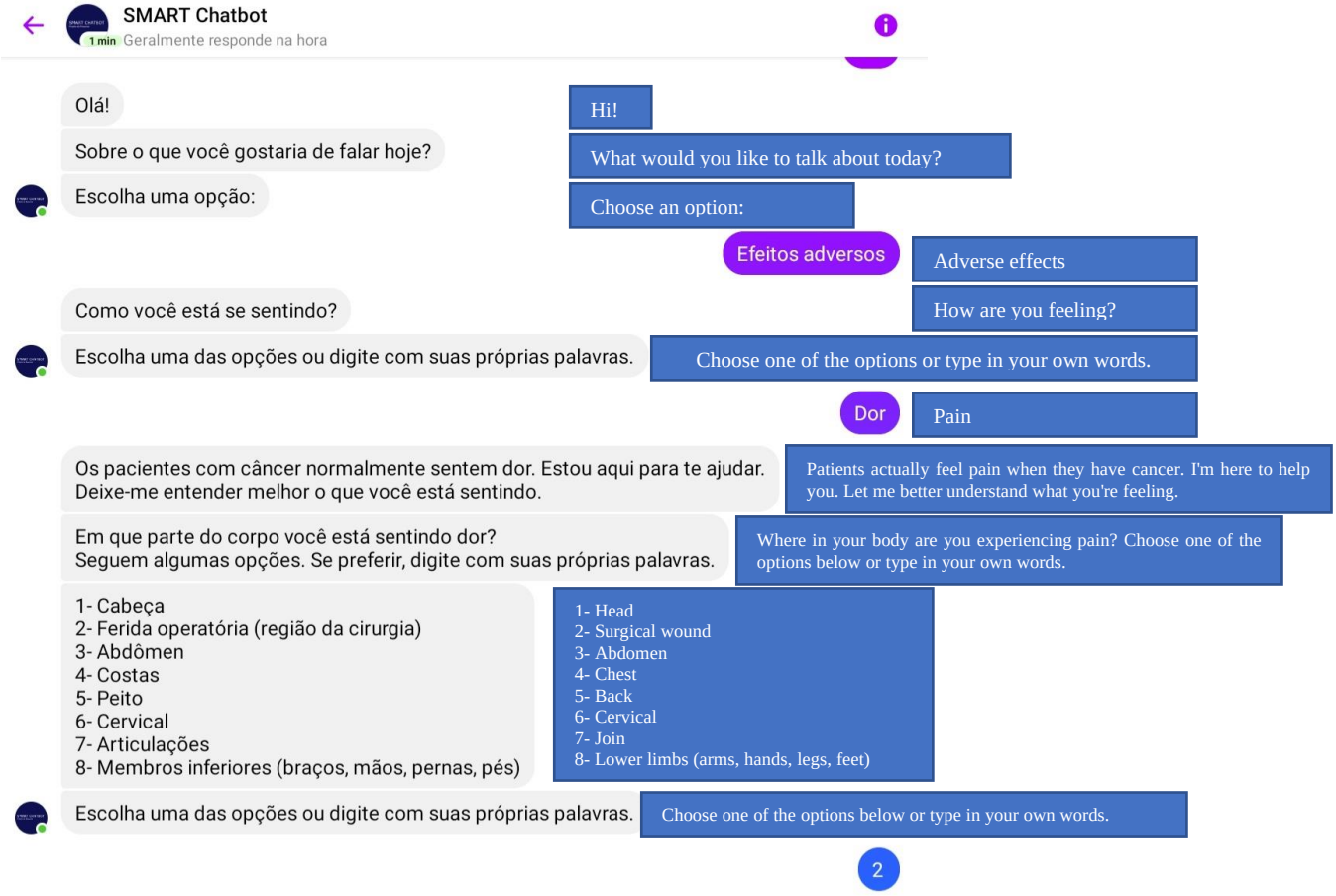
1) I think that I would like to use this chatbot frequently	**6)** I thought that there was too much inconsistency in this chatbot
2) I found the chatbot unnecessarily complex.	**7)** I imagine that most people would learn to use this chatbot very quickly.
3) I thought the chatbot was easy to use.	**8)** I found the chatbot very cumbersome/awkward to use.
4) I think that I would need the support of a technical person to be able to use this chatbot.	**9)** I felt very confident using the chatbot.
5) I found that the various functions in this chatbot were well integrated.	**10)** I needed to learn a lot of things before I could get going with this chatbot.

5.2.3 Chatbot

The model is described in sections 4.2 and 5.1. We included in the chatbot the main adverse effects resulting from the treatment of CRC patients, such as fever, pain, nausea and vomiting, dyspnea, insomnia, constipation, diarrhea, fatigue, loss of appetite, peripheral neuropathy, and hair loss (CARAYOL et al., 2019), (CHEONG et al., 2018), (SUN et al., 2017), (PARK et al., 2019); and some symptoms and signs of the disease, such as weight loss, anxiety, memory loss, and headache (LE et al., 2017), (CARLI et al., 2020), (CHUNG et al., 2019),

(KLAAS et al., 2018), (ARGILÉS et al., 2018). In addition, personalized physical activity is also suggested, following the doctor's guidance. The user interface is outlined in Figure 29.

Figure 29: Patient interface.



5.2.4 Data Analysis

Data analysis primarily consisted of descriptive statistics, and outcomes were mainly described in percentages or proportions, mean ± SD (standard deviation), or median (interquartile). Data were analyzed using the Microsoft® Excel® spreadsheet software (Office 365).

5.2.5 Ethical Aspects

Ethical approval was obtained for this study from the Ethical Committee of the Universidade do Vale do Rio dos Sinos (CAAE 48258421.7.0000.5344).

5.3 Prospective Non-randomized Clinical Study

This section presents the methodology of the prospective study, which aims to evaluate the benefits of applying the SMT model in colorectal cancer patients undergoing active treatment. It describes the type of study and the participants who participated, details how the intervention was carried out, and finally highlights the tool used for data analysis.

The results of applying the eating habits and physical activity questionnaire from the Food Guide: How to have a healthy diet – Ministry of Health (BRAZIL, 2013) before and after the intervention were published in the Journal: Research, Society and Development in June 2023.

- QUEIROZ, D.A. de; ASSUNÇÃO, G.S.A.; CARNEIRO, P.B.F.; ROSSINI, A.; SILVEIRA, E.F. da; QUEIROZ, E.A.I.F. de; COSTA, C.A. da. Evaluation of eating habits and practice of physical activity in colorectal cancer patients in the active phase of treatment. Research, Society and Development, [S. l.], v. 12, n. 6, p. e23112642155, 2023. DOI: https://doi.org/10.33448/rsd-v12i6.42155

In addition, the findings of a prospective non-randomized clinical study that developed and evaluated a new computational model for monitoring colorectal cancer patients in the active treatment phase were published in the Journal: Healthcare Analytics in September 2023.

- QUEIROZ, D.A. de; PASSARELLO, R.S.; MOURA-FÉ, V.V. de; ROSSINI, A.; SILVEIRA, E.F. da; QUEIROZ, E.A.I.F. de; COSTA, C.A. da. A wearable chatbot-based model for monitoring colorectal cancer patients in the active phase of treatment. Healthcare Analytics, Sep, 2023. DOI: https://doi.org/10.1016/j.health.2023.100257

5.3.1 Study Type

A prospective non-randomized clinical study that aims to evaluate the benefits of the SMT (Smart Monitoring Tool) model to patients regarding adverse effects, treatment, and quality of life. The study population was colorectal cancer patients undergoing active treatment at the Sinop Cancer Center (Cecans) in Sinop, Mato Grosso, Brazil. A municipality located in the north of MT, classified as one of the four largest cities in the state, with a population of 196,067 inhabitants (IBGE, 2023).

Data were collected from July 2022 to December 2022 at Cecans. Patients were divided into control and intervention groups. Patients in the intervention group were exposed to the proposed model, including using a chatbot and wearable device, and the control group was exposed to pre-existing monitoring. The outcome assessment was based on the comparison between the intervention group and the control group. All CRC patients met the inclusion criteria were invited to participate in the study. All data collected were from patients treated by the insurance classified as private. Data was collected using a smartphone application and wearable device made available to patients on the day of signing the Informed Consent Form and on the day of the first chemotherapy session, respectively.

5.3.2 Inclusion and Exclusion Criteria

Inclusion criteria were CRC patients; aged over 18 years old, under active cancer treatment; staging from I to IV; Patients must have smartphone skills. Exclusion criteria were patients with restrictions to exercise due to severe cardiovascular, pulmonary, or renal diseases, who have cognitive impairment that prevents using smartphones, or who cannot give verbal consent.

5.3.3 Model

The model is described in sections 4.2 and 5.1. Figure 30 shows an example of the peripheral neuropathy diagram.

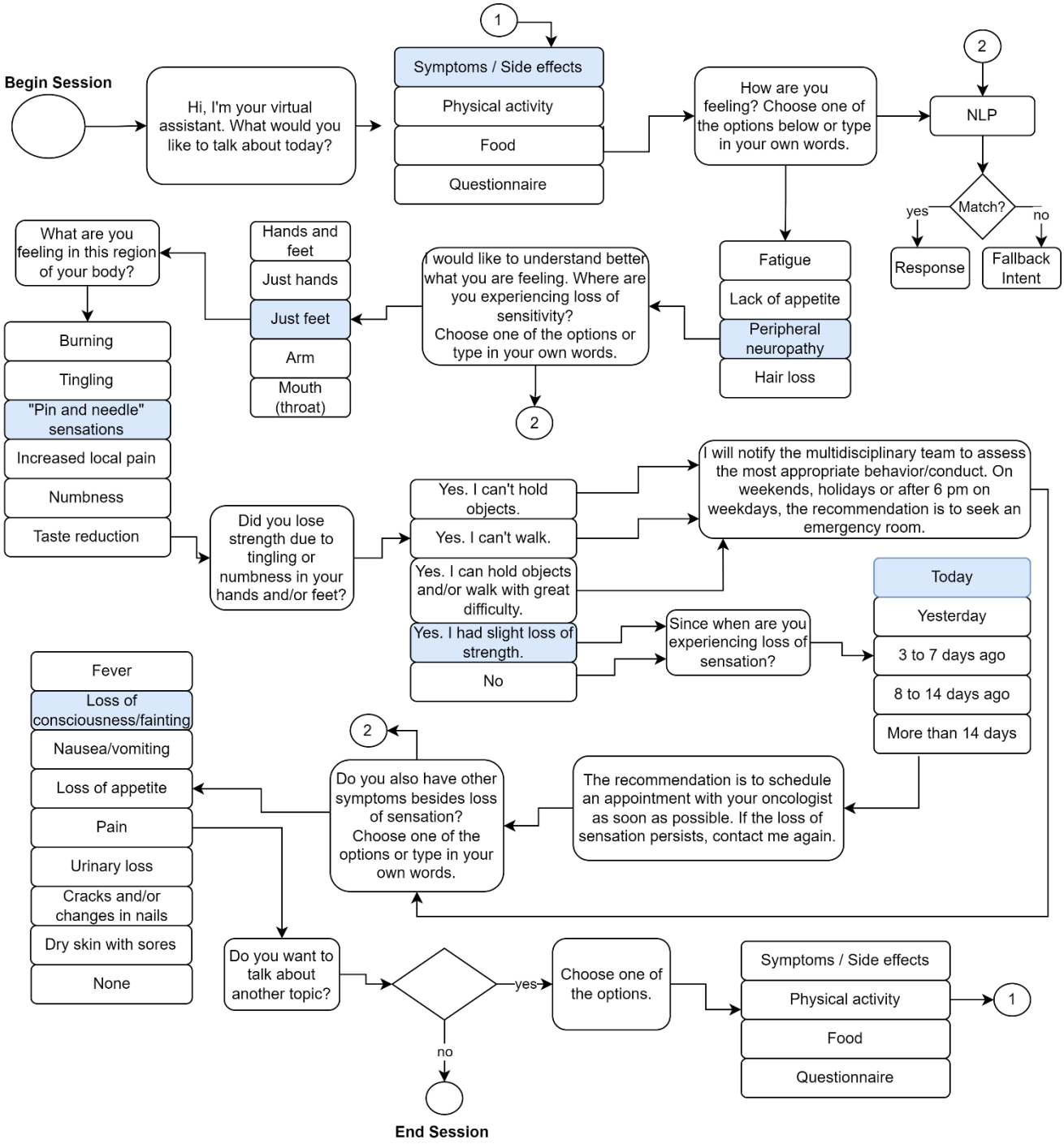
5.3.4 Intervention

Monitoring was carried out for 8 weeks from the 1st chemotherapy session. During this period, the participant was guided to use the application, the chatbot, and the wearable device and answer the questionnaires. The application addressed important information about the main signs and symptoms of cancer and the main adverse effects of the treatment.

Patients who met the inclusion criteria were invited to participate in the research during the 1st chemotherapy session. Patients who agreed to participate signed the Informed Consent Form. Patients were also informed that their participation in the study was voluntary and that they could withdraw at any time without changing their usual oncological care. Figure 31 shows the monitoring steps. The interval between chemotherapy sessions was usually 15 days. Week

0 was the day that patient monitoring began. The Quality of Life of Cancer Patients (QLQ-C30) and Colorectal (QLQ-CR29) surveys were applied in weeks 0, 4, and 8, that is, on the day of signing the Informed Consent Form, one month and two months later.

Figure 30: Example of diagram (peripheral neuropathy) built-in diagrams.net tool.



Patients were asked to answer a questionnaire containing 18 questions about eating habits and physical activity from the Food Guide: how to have a healthy diet – Ministry of Health (BRAZIL, 2013). The questionnaire was applied in the 1st chemotherapy session (week 0) and eight weeks after the first application (week 8). In the first application, patients were

instructed to self-report their eating habits and physical activity before the cancer diagnosis. And in the second application, patients were asked to self-report their conduct after participating in the research.

In weeks two and six, we exclusively clarified doubts and guided patients on using the app and the wearable device, if necessary. In the period between sessions, the patient interacted with the proposed model, which included using the chatbot and the wearable device. In week 8, participants were invited to evaluate usability and their experience with the model using the SUS (ISSOM et al., 2021), (STARA et al., 2021) and the UEQ (DENECKE; VAAHEESAN; ARULNATHAN, 2021), (TE PAS et al., 2020), (COTA et al., 2014). All data reported in these periods were recorded in a centralized database in real-time. Access to these data was limited to the Cecans nurse and the researchers responsible for the project.

Figure 32 highlights the actions that were performed between chemotherapy sessions. During this period, patients and their interactions with the model were monitored. In addition, depending on the criticality of the data reported by the patients, the outpatient multidisciplinary team was notified in real-time and contacted the patient to guide the most appropriate conduct.

In the chatbot, the patient can interact about signs, symptoms, perceived adverse effects, diet, and physical activity. During physical activities, participants were instructed to use the wearable device to automatically collect the number of steps and the walking distance. The patient was encouraged to answer the proposed surveys through the chatbot according to the pre-defined frequency. Based on the responses, the patient received feedback.

The data reported allowed researchers to monitor the use of the application in real-time. This architecture allowed, for example, to contact the multidisciplinary team that accompanies the participant in real time if the reported data showed a relevant deterioration in their clinical condition. If the use of the solution was lower than expected, participants received alerts encouraging the use and reminding them of the importance of using the SMT, as proposed. The engagement of participants was evaluated in several ways, such as the time of use of the application and the wearable device, and the quality of the data reported by the participants in the solution. The system gave feedback regarding the data provided. Feedback was customized according to the interaction performed.

Figure 31: Steps during patient monitoring on active treatment.

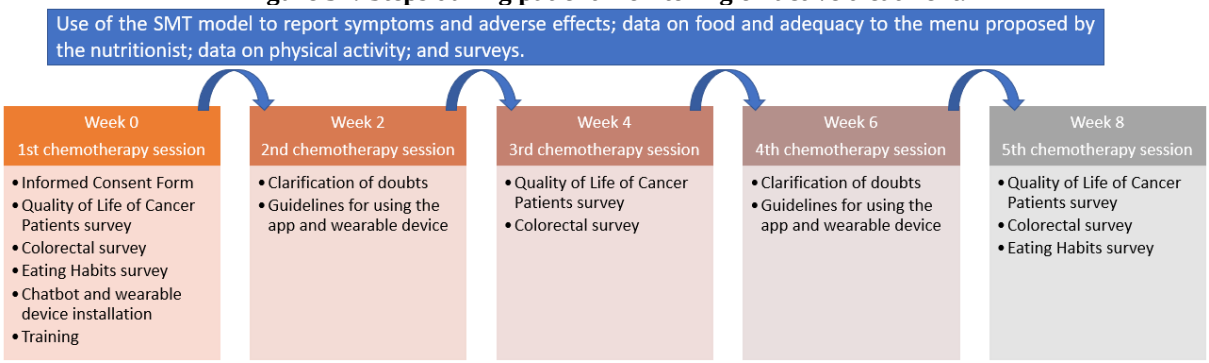
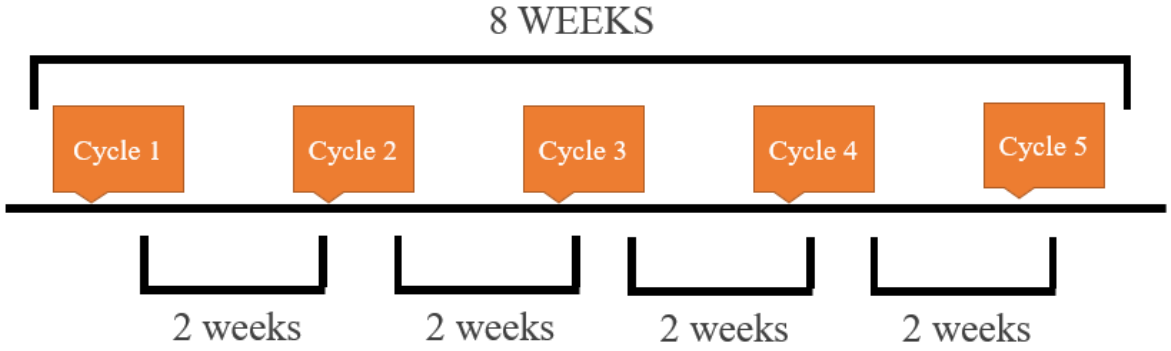


Figure 32: Actions performed between chemotherapy sessions.



- Patient monitoring
- Patient interaction with the model
- Interaction about signs, symptoms and adverse effects through the chatbot
- Measurement of physical activity data
- Interaction about food
- Application of surveys between chemotherapy sessions through the chatbot
- Feedbacks to patients based on their reports
- Sending notifications in case of non-interaction
- Notification of the Cecans multidisciplinary team due to the criticality of the patient's report

5.3.5 Risks and Benefits

The participant received application training to mitigate the risks, including a questionnaire and chatbot. The application was installed on the participant's smartphone after signing the Informed Consent Form (ICF) of participation in the research.

The risks related to the use of the smartphone application and its functionalities, including the questionnaire and chatbot, and the use of the wearable device may be associated with the lack of technological skills, in addition to the discomfort and shame of the participant. Also, emotional discomfort can be generated while using the application due to the participant's clinical status. The researcher could assist the participant and call the multidisciplinary team if

necessary. The participant could temporarily or permanently discontinue the use and interaction.

The risks arising from handling medical records can be losses and possible damage, so to avoid them, taking medical records occurred only at Cecans, and materials that could damage it, such as water, coffee, and other foods, were not consumed in place. Data collection from medical records was carried out exclusively by doctoral student Diogo Albino de Queiroz.

Risks arising from storing data collected through the application could be data loss due to hackers or unauthorized access to the database. To avoid these risks, access to the database was allowed only with personal authentication; each participant had a personal password to access the application. In addition, the stored data was anonymized.

As a benefit, research participants indirectly contributed to collecting data that helped to better understand the effects of cancer and its treatment. They also contributed to validating a new model for monitoring CRC patients undergoing active treatment. Directly, the participants received guidance on signs and symptoms resulting from the disease and the adverse effects of the treatment, in addition to guidance on the practice of physical activities.

5.3.6 Term of Consent and Training of the Patient

All patients diagnosed with CRC undergoing treatment at Cecans were invited to participate in the research. During the chemotherapy session, the scope of the study and the Informed Consent Form (ICF) were presented. At this moment, patients who agreed to participate signed the ICF with the responsible researcher. A copy of the ICF was given to the participant. Furthermore, the application was installed on the participant's smartphone on the same day, and the training was carried out. Finally, the Quality of Life of Cancer Patients (QLQ-C30) and Colorectal surveys (QLQ-CR29) were applied. The estimated time for installing and training the application and applying the surveys was 60 minutes (1 hour).

Given the declaration by the World Health Organization (WHO) on January 30, 2020, considering the outbreak of the disease caused by the new coronavirus (COVID-19) as a Public Health Emergency, sanitary measures were adopted with the use of alcohol gel to hands, mask, face shield, and distance were maintained when the researcher meets with the research participants.

5.3.7 Data Analysis

In this step, we evaluated the proposed model's influence on patients' clinical conditions. For this, patients' data were divided into two groups:

- Control Group (pre-existing monitoring): colorectal cancer patients who used traditional monitoring during the active cancer treatment phase.
- Intervention Group (new monitoring): colorectal cancer patients who used the monitoring proposed in this study.

Subsequently, the following data were evaluated between these two groups: physical activity, occurrence of adverse effects, and quality of life. In addition, in the monitoring group, the use of the Smart Monitoring Tool (chatbot, wearable device, questionnaires, interaction with the chatbot) and the influence of the SMT model on the patient's eating habits and physical activity were evaluated.

Statistical analysis: Data were presented as mean ± standard deviation (SD), median (interquartile), or percentage (%). The results were statistically evaluated by the Student's t test, the Wilcoxon test, or the chi-square test (χ^2) using the GraphPad Prism 7 Program. The minimum acceptable significance level was $p < 0.05$.

5.3.8 Ethical Aspects

Ethical aspects are considered by Resolution 466/12 of the Ministry of Health, which establishes ethical standards governing research involving human beings. The execution of the project was authorized by Cecans and by the physicians responsible for the Oncology Wing and approved by the Ethics Committee in Research with Human Beings (CAAE 48258421.7.0000.5344). All patients provided written informed consent to participate in the study.

5.4 Case Study

This section presents the methodology, study type, and participants, and details how the intervention was carried out.

5.4.1 Study Type and Participants

The case study aims to evaluate the SMT model joined to the recommender system. The SMT model has some predefined feedback based on flowcharts. However, in the recommender system, feedback is evaluated by users to improve the assertiveness and accuracy of the proposed recommendations. Thus, feedback is expected to address more patients' needs during treatment. In this study, we simulated the behavior of the model integrated into the recommender system using real examples of interactions performed by patients during the intervention period of application of the SMT model.

5.4.2 Intervention

The project team worked closely with the clinic's multidisciplinary team (doctors, nurses, and pharmacists) to map the main symptoms and adverse effects reported by patients during the application of the SMT model. The study consisted of identifying the symptoms and adverse effects self-reported by patients during the period of chemotherapy treatment (phase 1), discussion and map of the most common guidelines given by the medical team during this period (phase 2), technical development (phase 3) and simulation of patient interactions using the recommendation system integrated into the SMT model (phase 4), as shown in Figure 33.

In phase 1, all adverse effects and symptoms self-reported by patients who participated in the SMT model intervention were identified and listed. During the SMT model intervention, from July to December 2022, all patients who met the inclusion criteria were invited to participate in the study. In phase 2, the project team interviewed the clinical staff (physicians, nurses, pharmacists) and analyzed medical records to map out the most common recommendations to patients who participated in the study. In addition, adverse effects common to colorectal cancer treatment protocols, which in this patient sample were not reported, were discussed and included.

In phase 3, the recommender system architecture was designed and integrated into the SMT model, as presented in Figure 14. Thus, the expectation is that this new architecture addresses personalized recommendations that meet patients' expectations in a more assertive and precise way. In phase 4, all interactions of two patients who participated in the SMT model intervention were selected. Thus, these interactions regarding the self-report of symptoms and adverse effects were simulated in the new architecture, which includes the recommendation system. For each interaction, an evaluation of the proposed recommendation was simulated,

using the Linkert scale from 1 to 5 (1 represents a more negative evaluation, 3 is neutral, and 5 is a more positive evaluation) to verify the addressing of the patient's expectations.

Figure 33: Process of conception and development of the case study.

Phase 1: Identify the symptoms and adverse effects self-reported by patients during the period of chemotherapy treatment.	
Application of the SMT model	Participants: colorectal cancer patients; aged over 18 years old, under active cancer treatment; staging from I to IV; Patients must have smartphone skills.
Study period	Patient follow-up for 8 weeks from the 1st chemotherapy session from July to December 2022.
Phase 2: Discuss and map the most common guidelines given by the medical team in this period.	
Recommendations	Interview with clinical staff and analysis of medical records to identify recommendations given to patients during the intervention period.
Phase 3: Technical development.	
Recommender system	Recommender system architecture design.
Phase 4: Simulate patient interactions using the recommendation system built into the SMT model.	
Case study	Evaluation of how the recommender system would address the recommendations when integrated into the SMT model.

6 RESULTS AND DISCUSSION

This chapter presents the results and discussion of the pilot, prospective and case studies.

6.1 Pilot Study

This section describes the results obtained after applying the model to the Cecans team, evaluating its usability and user experience. Based on these results, we updated and complemented the model, then applied the model to CRC patients.

6.1.1 Results

Nurses, pharmacist, psychologist, nutritionist, and the clinic's administrative staff who have direct or indirect contacts with patients during the treatment phase participated in the testing period. Due to having contributed during the chatbot construction stage with suggestions and having validated the system's features, physicians do not participate in the tests. A total of 13 participants participated in the survey, corresponding to 81.25% of the team. All clinic staff participated in the study except for physicians and one administrative staff member who was in the home office.

Demographic information for the 13 participants is presented in Table 10. Most participants were female (12/13, 92.31%), with a mean age of 32.69 (SD 9.61; range: 22-53 years). Most participants were graduates (4/13, 30.77%) or postgraduates (7/13, 53.85%), white/Caucasian (7/13, 53.85%), and younger than 30 years (7/13, 53.85%).

Table 10: Demographic data of participants.

Variable	Participants (n=13)
Gender, n (%)	
Female	12 (92.31)
Male	1 (7.69)
Age Range, n (%)	
≤ 30	7 (53.85)
> 30	6 (46.15)
Age (years)	
Mean (SD)	32.69 (9.61)
Education, n (%)	
Other	2 (15.38)
Graduate	4 (30.77)
Postgraduate	7 (53.85)
Ethnicity, n (%)	
White/Caucasian	7 (53.85)
Hispanic or Latino	5 (38.46)
Indigene	1 (7.69)

The chatbot scored high on all UEQ scales. Scores were above the benchmark and are graphically represented in Figure 34, indicating that users' expectations were addressed. This study's attractiveness and efficiency scales were rated at 1.88 and 2.08, with the benchmark considered excellent above 1.84 and 1.88, respectively. The perspicuity, dependability, stimulation, and novelty scales were rated at 1.83, 1.58, 1.54, and 1.31, respectively. The scales were within the range considered good in evaluating the UEQ benchmark.

Figure 34: Chatbot UEQ scores against benchmark.

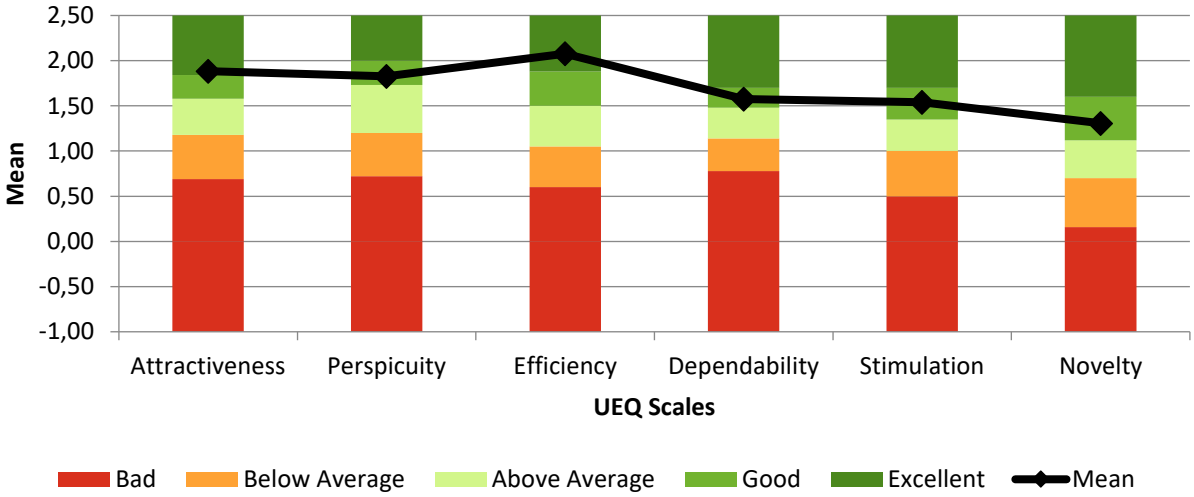


Figure 35 represents the mean and the confidence interval per scale. The range of the scales is between -3 and +3 (DENECKE; VAAHEESAN; ARULNATHAN, 2021). Scale values above 0.8 represent a positive evaluation, values between -0.8 and +0.8 represent a neutral evaluation, and values below -0.8 represent a negative evaluation. Thus, it was observed that all scales presented values greater than 1, representing a positive evaluation of the chatbot. The mean of attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty scales were evaluated at 1.88 (variance 0.42), 1.83 (variance 1.26), 2.08 (variance 0.70), 1.58 (variance 0.43), 1.54 (variance 1.39) and 1.31 (variance 0.73), respectively.

Figure 36 represents the distributions of responses in the UEQ by item. The results show that most participants considered the chatbot innovative, friendly, efficient, enjoyable, secure, fast, attractive, among others. The scale ranges from 1 to 7, where 1 represents a more negative evaluation, 4 neutral, and 7 a more positive evaluation. The colors represent the intensity of each rating scale.

Participants assessed usability through the SUS. The mean SUS score was 75 ± 7.14, and the median was 72.5 (70-77.5), indicating a usable system. SUS scores above 68 indicate

that the system has acceptable usability (OH et al., 2020), (BANGOR; KORTUM; MILLER, 2008), (ISSOM et al., 2021).

Figure 35: The mean and the confidence interval per scale.

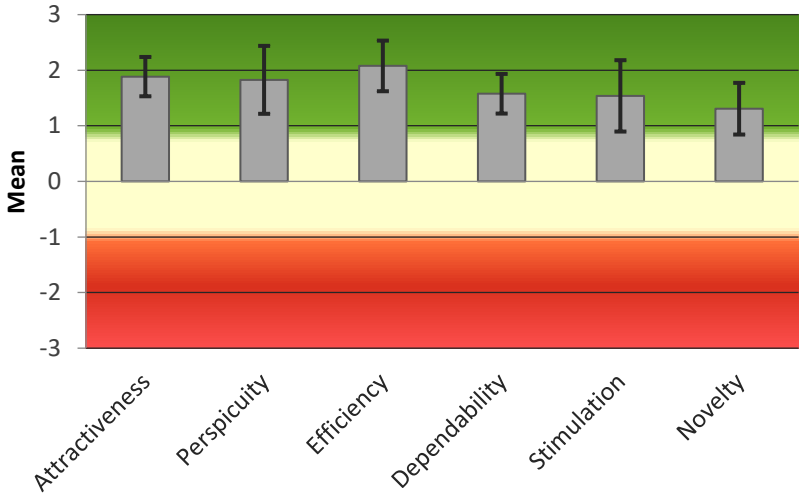


Table 11 shows each statement evaluated's mean, standard deviation, median and interquartile range. This analysis's minimum and maximum values are 0 and 4, respectively. The mean of most statements was above 3 (6/10, 60%), 90% (9/10) had a median of 3, and 80% (8/10) of statements had 75% (interquartile) of their ratings equal to or above 3. The evaluation score was normalized, where 0 and 4 mean a negative and positive evaluation of each survey statement, respectively.

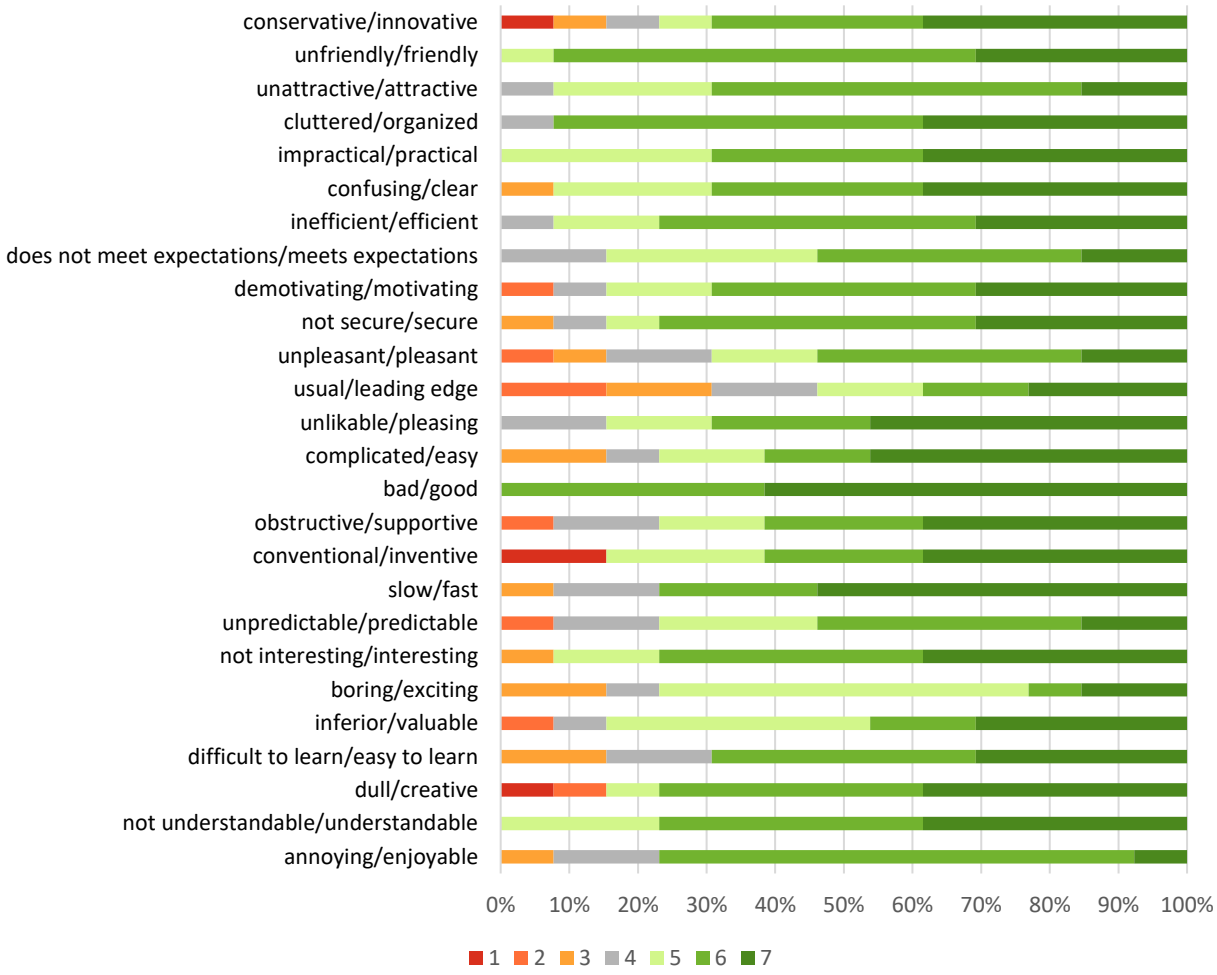
6.1.2 Discussion

In the present study, we observed that the chatbot provided users a good experience and usability. It was highly rated in both the UEQ and SUS questionnaires. All the participants' scores on the UEQ scales were rated as good or excellent (Figure 34), suggesting they were satisfied with the chatbot experience. The evaluation of attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty scales evaluated by the participants had ratings above +0.8, indicating that they had a positive experience using the chatbot (Figure 35).

The results show that most participants considered the chatbot innovative, friendly, efficient, enjoyable, secure, fast, attractive, among others. Similarly, patients evaluated the chatbot as more practical, efficient, innovative, pleasurable, fast, and attractive than conventional questionnaires (TE PAS et al., 2020). Hauser-Ulrich et al. highlighted that participants criticized the lack of free text answers and an overly static interaction flow

(HAUSER-ULRICH et al., 2020). On the other hand, our chatbot included several questions that allow free text answers and personalized flows according to the responses provided.

Figure 36: Distribution of Answers per Item.



Furthermore, the mean SUS score was 75, and the median was 72.5. The SUS score of most participants was above 68 (10/13, 76.92%), and only 3 (23.08%) rated it equal to 67.5, suggesting that the individual usability assessment was also assessed as acceptable. Similarly, Piau et al. demonstrated the feasibility of using the chatbot to collect symptom data from cancer patients undergoing chemotherapy (PIAU et al., 2019). Issom et al. presented the feasibility of using the chatbot to support self-management in adult or young adult patients diagnosed with sickle cell disease (ISSOM et al., 2021). In addition, the chatbot proved feasible to collect linked data from the population to study the relationship personal characteristics, diet, and physical activity in the prevalence of obesity and overweight (ASENSIO-CUESTA et al., 2022).

The SUS survey applied indicated that the usability addresses participants' expectations. As seen in Table 11, most of the items evaluated had a mean and median equal to or greater

than 3 (minimum and maximum values are 0 and 4, respectively). In addition, the interquartile of 80% of the items evaluated were equal to or above 3. Most participants thought other people would learn to use the chatbot very quickly. In addition, they would like to use the chatbot frequently and find it easy to use. Participants evaluated that they had sufficient knowledge and would not need technical support to use the chatbot.

Table 11: Responses to individual system usability statements.

Statement	Mean	Standard Deviation	Median	Interquartile (25-75%)
1. I think that I would like to use this chatbot frequently	2,77	0,73	3,00	3 - 3
2. I found the chatbot unnecessarily complex	2,46	1,20	2,00	2 - 3
3. I thought the chatbot was easy to use	3,08	0,49	3,00	3 - 3
4. I think that I would need the support of a technical person to be able to use this chatbot	3,38	0,65	3,00	3 - 4
5. I found that the various functions in this chatbot were well integrated	2,92	0,95	3,00	2 to 4
6. I thought that there was too much inconsistency in this chatbot	3,00	0,71	3,00	3 to 3
7. I imagine that most people would learn to use this chatbot very quickly	3,15	0,55	3,00	3 to 3
8. I found the chatbot very cumbersome / awkward to use	3,23	0,73	3,00	3 to 4
9. I felt very confident using the chatbot	2,77	0,44	3,00	3 to 3
10. I needed to learn a lot of things before I could get going with this chatbot	3,23	0,60	3,00	3 to 4

Source: elaborated by the authors.

Stara et al. demonstrated that people found that most of the conversational agent's functionality could be learned quickly and that the tool was easy to use and well-integrated, which corroborates our findings (STARA et al., 2021). Studies have evaluated chatbots as highly usable due to their simple and familiar user interface (ISSOM et al., 2021), (HOLMES et al., 2019). However, Oh et al. showed that patients rated the usability of using the traditional methodology better than the chatbot, although the difference was not significant, indicating that depending on the context, paperback books could be more attractive and accepted (OH et al., 2020).

The chatbot included information and guidance on more than 10 signs and symptoms and/or adverse effects, such as fever, pain, headache, nausea and vomiting, dyspnea, insomnia, constipation, diarrhea, fatigue, loss of appetite, and peripheral neuropathy. In addition, it allowed interactions about physical activities, food, nutritionist recommendations and, finally,

addressed the QLQ-CR29 and QLQ-C30 questionnaires developed by the EORTC. The features include the main symptoms reported by cancer patients listed by Piau et al., loss of appetite, fatigue, difficulty in performing daily activities, and abnormal sensitivity in the extremities (PIAU et al., 2019). Chaix et al. showed that breast cancer patients had better medication adherence through the chatbot (CHAIX et al., 2019). The chatbot proved to be a helpful healthcare tool for collecting relevant data from populations at risk of overweight and obesity (ASENSIO-CUESTA et al., 2022). In this perspective, we believe that the use of the chatbot contributes to better adherence to the nutritionist's recommendations and the performance of physical activities proposed by the doctor, as well as contributes to improving the management of the signs and symptoms manifested by patients undergoing treatment.

6.2 Prospective Non-randomized Clinical Study

In this section, we describe the results of the SMT model application in CRC patients in the active treatment phase, demonstrating the clinical and epidemiological profile of the participants, use of the model, incidence of symptoms and adverse effects, physical exercise practice, user experience, system usability, and eating habits.

6.2.1 Results

In all, 36 patients were invited to participate in the research, 19 in the intervention group and 17 in the control group. In the control group, all patients agreed to participate and remained until the conclusion of the research. In the intervention group, four patients did not accept to join because they did not have technological skills or were not interested in participating, and two patients withdrew during the research due to complications resulting from the treatment. The mean age of these patients was 58.2 years old, and most patients (83.3%) were over 50 years old. Furthermore, three patients reported difficulties in dealing with technology but agreed to participate and remained in the study. Finally, 13 patients completed the intervention in the intervention group.

6.2.1.1 Clinical and Epidemiological Profile of Control and Intervention Group of CRC Patients

According to the epidemiological data in Table 12, there were no statistical differences between the control and intervention groups, demonstrating similarity between the groups. A total of 30 patients participated in the study, 17 in the control group and 13 in the intervention group. Mean body weight, body mass index, oximetry, and age in the control group were 76.5 kg, 26.9 kg/m², 96.9% and 50.8 years old, respectively, and 73.8 kg, 26.1 kg/m², 97.0 % and 49.7 years old in the intervention group. Furthermore, height and temperature medians were 1.7m (1.605 –1.745) and 36.3°C (36.2 – 36.4), respectively, in the control group, and 1.68m (1.615 – 1.70) and 36.4ºC (36.3 – 36.4) in the intervention group. Regarding blood pressure, the mean systolic blood pressure was 121.2 (SD 19.3) mmHg, and the median diastolic pressure was 80 (70 – 90) mmHg, both in the control group and 123.8 (SD 16.1) mmHg and 80 (80 – 80) mmHg, respectively, in the intervention group.

Table 12: Distribution of patients with colorectal cancer in the control and intervention groups, according to epidemiological characteristics.

Variable	Control	Intervention	Total	*p*
n (%)	**17 (56.7)**	**13 (43.3)**	**30 (100)**	
Body Weight (kg) (mean ± SD)	76.5 ± 13.9	73.8 ± 12.1	75.3 ± 13.0	0.5843
Body Mass Index (kg/m²) (mean ± SD)	26.9 ± 3.7	26.1 ± 3.3	26.6 ± 3.5	0.5461
Height (m) (median (IQ)) [#]	1.7 (1.605 – 1.745)	1.68 (1.615 – 1.7)	1.68 (1.618 – 1.725)	0.6417
Temperature (°C) (median (IQ)) [#]	36.3 (36.2 – 36.4)	36.4 (36.3 – 36.4)	36.35 (36.28 – 36.4)	0.0615
Oximetry (%) (mean ± SD)	96.9 ± 1.11	97.0 ± 1.35	96.9 ± 1.2	0.7957
Systolic Blood Pressure (mmHg) (mean ± SD)	121.2 ± 19.3	123.8 ± 16.1	122.3 ± 17.8	0.6905
Diastolic Blood Pressure (mmHg) (median (IQ)) [#]	80 (70 – 90)	80 (80 – 80)	80 (70 – 90)	0.8339
Age (mean ± SD)	50.8 ± 13.5	49.7 ± 13.9	50.3 ± 13.4	0.8238
Age Range (n (%))	**n (%)**	**n (%)**	**n (%)**	
25 to 44	7 (41.2)	6 (46.2)	13 (43.3)	0.7583
45 to 59	4 (23.5)	4 (30.8)	8 (26.7)	
60 to 100	6 (35.3)	3 (23.1)	9 (30.0)	
Gender[&]	**n (%)**	**n (%)**	**n (%)**	
Female	5 (29.4)	8 (61.5)	13 (43.3)	0.1376
Male	12 (70.6)	5 (38.5)	17 (56.7)	
Marital Status[&]	**n (%)**	**n (%)**	**n (%)**	
Married	15 (88.2)	12 (92.3)	27 (90.0)	>0.9999
Divorced/Single	2 (11.8)	1 (7.7)	3 (10.0)	

Ethnic	**n (%)**	**n (%)**	**n (%)**	
White	7 (41.2)	5 (38.5)	12 (40.0)	0.5083
Hispanic	10 (58.8)	7 (53.8)	17 (56.7)	
Black	0 (0.0)	1 (7.7)	1 (3.3)	
City	**n (%)**	**n (%)**	**n (%)**	
Sinop-MT	8 (47.1)	5 (38.5)	13 (43.3)	0.3910
Sorriso-MT	5 (29.4)	2 (15.4)	7 (23.3)	
Others	4 (23.5)	6 (46.2)	10 (33.3)	
Place of Birth	**n (%)**	**n (%)**	**n (%)**	
Paraná	7 (41.2)	3 (23.1)	10 (33.3)	0.5658
Rio Grande do Sul	4 (23.5)	2 (15.4)	6 (20.0)	
Santa Catarina	2 (11.8)	1 (7.7)	3 (10.0)	
Mato Grosso	1 (5.9)	2 (15.4)	3 (10.0)	
Others	3 (17.6)	5 (38.5)	8 (26.7)	
Region of Place of Birth	**n (%)**	**n (%)**	**n (%)**	
South Region	13 (76.5)	6 (46.2)	19 (63.3)	0.1412
Midwest Region	3 (17.6)	3 (23.1)	6 (20.0)	
Others	1 (5.9)	4 (20.8)	5 (16.7)	

Results are expressed as the number of individuals and percentage (n (%)) Age Range, Gender, Marital Status, Ethnic, City, Place of Birth, Region of Place of Birth; Results expressed as mean Body Weight, Body Mass Index, Oximetry, Systolic Blood Pressure, Age; Results expressed as median Height, Temperature, Diastolic Blood Pressure; SD = standard deviation; IQ = interquartile; Statistical analysis: Student t test (unpaired), # Mann-Whitney test, Chi-square test and &Fisher test. Source: elaborated by the authors.

Most patients in both groups were between 25 and 44 years old (control: 41.2%; intervention: 46.2%), were married (control: 88.2%; intervention: 92.3%), and Hispanic (control: 58.8%; intervention: 53.8%). Most patients were men (70.6%) in the control group and women (61.5%) in the intervention group. Most patients living in Sinop-MT (control: 47.1%; intervention: 38.5%) and Sorriso-MT (control: 29.4%; intervention: 15.4%) were in both groups. Most patients were born in the Southern region of Brazil (control: 76.5%; intervention: 46.2%) since the colonizers and the first immigrants from Sinop came mainly from the southern region. Sinop is located in the Midwest region.

According to the clinical data in Table 13, most patients were diagnosed with stage 3 cancer (control: 52.9%; intervention: 69.2%), had a family history of cancer (control: 47.1%; intervention: 69.2%), and had surgery and chemotherapy as indicated therapy (control: 82.4%; intervention: 76.9%), with adjuvant chemotherapy (control: 64.7%; intervention: 69.2%). The mFolfox6 protocol (control: 41.2%; intervention: 69.2%) was the most recommended. Most patients, both in the control and intervention groups, had adenocarcinoma-type CRC (control: 100.0%; intervention: 100.0%), had affected lymph nodes (control: 58.8%; intervention:

76.9%), were diagnosed with primary cancer (control: 88.2%; intervention: 92.3%), and did not have metastasis (control: 70.6%; intervention: 92.3%). No statistical difference was identified between the groups regarding clinical and epidemiological characteristics, which demonstrates the similarity and homogeneity of the control and intervention groups.

Table 13: Distribution of patients with colorectal cancer in the control and intervention groups, according to clinical characteristics.

Variable	Control	Intervention	Total	*p*
Colorectal cancer type	**n (%)**	**n (%)**	**n (%)**	
Adenocarcinoma	17 (100.0)	13 (100.0)	30 (100.0)	
Staging	**n (%)**	**n (%)**	**n (%)**	
2	3 (17.6)	3 (23.1)	6 (20.0)	0.3376
3	9 (52.9)	9 (69.2)	18 (60.0)	
4	5 (29.4)	1 (7.7)	6 (20.0)	
Staging (group)[&]	**n (%)**	**n (%)**	**n (%)**	
1 and 2	3 (17.6)	3 (23.1)	6 (20.0)	> 0.9999
3 and 4	14 (82.4)	10 (76.9)	24 (80.0)	
Family History	**n (%)**	**n (%)**	**n (%)**	
Yes	8 (47.1)	9 (69.2)	17 (56.7)	0.4759
No	7 (41.2)	3 (23.1)	10 (33.3)	
N/C	2 (11.8)	1 (7.7)	3 (10.0)	
Treatment Type	**n (%)**	**n (%)**	**n (%)**	
Chemotherapy	2 (11.8)	0 (0.0)	2 (6.7)	0.3170
Chemotherapy + Radiotherapy	0 (0.0)	1 (7.7)	1 (3.3)	
Surgery + Chemotherapy	14 (82.4)	10 (76.9)	24 (80.0)	
Surgery + Chemotherapy + Radiotherapy	1 (5.9)	2 (15.4)	3 (10.0)	
Treatment	**n (%)**	**n (%)**	**n (%)**	
Neoadjuvant	1 (5.9)	2 (15.4)	3 (10.0)	0.5197
Adjuvant	11 (64.7)	9 (69.2)	20 (66.7)	
Palliative	5 (29.4)	2 (15.4)	7 (23.3)	
Protocol	**n (%)**	**n (%)**	**n (%)**	
mFolfox6	7 (41.2)	9 (69.2)	16 (53.3)	0.6325
mFolfox6/Avastin	1 (5.9)	1 (7.7)	2 (6.7)	
mFolfox6/Cetuximab	1 (5.9)	0 (0.0)	1 (3.3)	
Folfiri/Bevacizumab	2 (11.8)	1 (7.7)	3 (10.0)	
Folfiri/Cetuximab	2 (11.8)	0 (0.0)	2 (6.7)	
5FU/HDLV	3 (17.6)	2 (15.4)	5 (16.7)	
Xelox/Capecitabine	1 (5.9)	0 (0.0)	1 (3.3)	
Primary Cancer[&]	**n (%)**	**n (%)**	**n (%)**	

Yes	15 (88.2)	12 (92.3)	27 (90.0)	>0.9999
No	2 (11.8)	1 (7.7)	3 (10.0)	
Metastasis[&]	**n (%)**	**n (%)**	**n (%)**	
Yes	5 (29.4)	1 (7.7)	6 (20.0)	0.1961
No	12 (70.6)	12 (92.3)	24 (80.0)	
Affected Lymph Nodes	**n (%)**	**n (%)**	**n (%)**	
Yes	10 (58.8)	10 (76.9)	20 (66.7)	0.3675
No	5 (29.4)	3 (23.1)	8 (26.7)	
N/C	2 (11.8)	0 (0.0)	2 (6.7)	

Results are expressed as the number of individuals and percentage (n (%)). Statistical analysis: Chi-square test and [&]Fisher test. Source: elaborated by the authors.

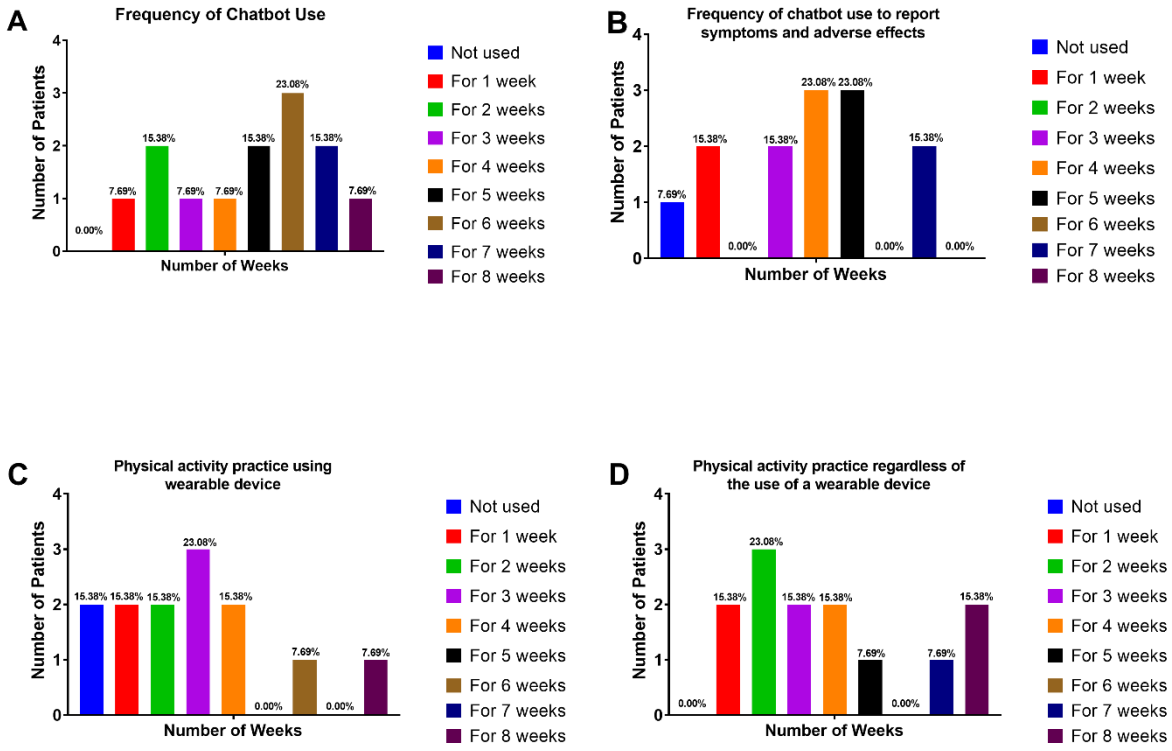
6.2.1.2 Evaluation of the Use of the Model

Most patients used the chatbot to report signs and symptoms, nutrition data, and physical activity records for at least 4 of the 8 intervention weeks (9 patients; 69.22%). Some patients used it for 1 or 2 weeks (3 patients; 23.07%); 3 or 4 weeks (2 patients; 15.38%); 5 or 6 weeks (5 patients; 38.46%), and 7 or 8 weeks (3 patients; 23.07%), as shown in Figure 37A. Figure 37B shows that most patients reported symptoms and adverse effects in an average of 4 weeks out of 8 weeks (8 patients; 61.54%), and only 1 patient (7.69%) did not report. The frequency of wearable device use was also mostly for 3 to 4 weeks (5 patients; 38.46%), with two patients (15.38%) reporting no use during the intervention period, as shown in Figure 37C. In addition, 7 (53.85%) patients physical activity practiced at least 3 of the eight weeks of intervention.

6.2.1.3 Evaluation of the Physical Activity Practice

Most patients in the intervention group were sedentary before diagnosis, 5 (38.46%) reported practicing physical activity, and 8 (61.54%) did not. During the intervention, it was observed that all patients performed physical activity for at least one week, 3 patients (23.08%) did it for 7 to 8 weeks, and four patients (30.76%) did it in most of the weeks of their participation in the research, as shown in Figure 37D. Furthermore, 5 patients reported performing physical activity regularly after starting treatment, and two said performing it occasionally. In the control group, 11 (64.7%) patients reported performing physical activity before diagnosis. However, after treatment, 5 (29.4%) patients said they continued practicing physical activity regularly.

Figure 37: (A) Frequency of chatbot use during the intervention. (B) Frequency of chatbot use to report symptoms and adverse effects. (C) The number of weeks participants engaged in physical activity using the wearable. (D) The number of weeks participants engaged in physical activity, regardless of wearable device use.



Regarding the number of patients who practiced some physical activity while participating in the intervention group, in weeks 1, 2, 4, and 7, 5 patients (38.5%) used the wearable device; in week 8, there were six patients (42.9%); in weeks 3, 5 and 6, there were 30.8%, 23.1%, and 30.8%, respectively. Considering the performance of physical activities with or without the use of the wearable device, 7 patients (53.8%) practiced some physical activity in weeks 4, 7, and 8, 8 patients (61.5%) practiced in week 6, and in weeks 1, 2, 3, and 5, there were 42.9%, 38.5%, 30.8%, and 42.9%, respectively (Table 14).

6.2.1.4 Evaluation of the Food Intake

Among the patients who reported how their food intake was during treatment, 6 (60%) patients mentioned a reduction in the amount of food consumed in at least one of the weeks of the intervention period, 2 (20%) reported that they maintained the same level of food intake and 2 (20%) increased the number of meals consumed. Among these reports, only one patient reported two different behaviors during the intervention period; in one of the weeks, the patient reported eating less than usual. Approximately one month later, the patient described eating

more than usual. Of the 13 participants in the intervention group, 9 (69.23%) patients reported their eating levels.

Table 14: Number of patients who performed physical activity in each week of participation in the research.

Variable	Intervention (With the use of a wearable device)	Intervention (With/without the use of a wearable device)	*p*
Practice of physical Activity	**n (%)**	**n (%)**	
Week 1	5 (38.5)	6 (42.9)	0.9896
Week 2	5 (38.5)	5 (38.5)	
Week 3	4 (30.8)	4 (30.8)	
Week 4	5 (38.5)	7 (53.8)	
Week 5	3 (23.1)	6 (42.9)	
Week 6	4 (30.8)	8 (61.5)	
Week 7	5 (38.5)	7 (53.8)	
Week 8	6 (42.9)	7 (53.8)	

Results are expressed as the number of individuals and percentage (n (%)). Statistical analysis: Chi-square test. Source: elaborated by the authors.

6.2.1.5 Analysis of Patient Interactions with the Model

Table 15 shows the number of interactions performed and how many patients interacted with each item. Regarding food, 10 (50.0%) notifications indicated a reduction in the usual diet, and 5 (25.0%) reported the maintenance or increase in the diet. In total, 6 (46.1%) patients who participated in the intervention said a reduction in food consumption at least once during their participation in the research, 2 (15.4%) reported maintaining their regular consumption, and 2 (15.4%) increased their everyday consumption. During the intervention, a total of 11 (84.6%) patients reported having practiced walking at least once during the research period, 6 (46.1%) patients reported having performed other activities, such as bodybuilding, beach tennis, and cycling, and 6 (46.1%) patients reported not being able to perform physical activity in at least one of the intervention weeks.

The adverse effect most referred by the patients was muscle fatigue (13 interactions; 30.2%), described by 7 (53.8%) patients. Loss of appetite (6 interactions; 13.9%) was the second most described symptom, followed by loss of sensation (peripheral neuropathy), constipation, and fatigue related to shortness of breath (5 interactions; 11.6%). Only one patient (7.7%) reported pain during the research.

In total, 6 (46.1%) patients completed the colorectal cancer survey once during the intervention. In this survey, patients reported having abdominal and buttock pain, dysuria, hair loss, and taste. In addition, 6 (46.1%) patients completed the Quality of Life of Cancer Patients survey at least once during their survey participation. The most cited symptoms were fatigue (20.5%), nausea and vomiting (20.5%), and constipation (20.5%), followed by pain (12.8%), loss of appetite (10.3%), insomnia (7.7%), and diarrhea (7.7%).

Table 15: Distributions of patient interactions and how many patients interacted in each subject.

Variable	Total Interactions	Number of Patients Who Interacted
Food	**n (%)**	**n (%)**
Less	10 (50.0)	6 (46.1)
Same	5 (25.0)	2 (15.4)
More	5 (25.0)	2 (15.4)
Physical Activity	**n (%)**	**n (%)**
Walking	61 (74.4)	11 (84.6)
Others (Bodybuilding, Beach Tennis, Cycling)	15 (18.3)	6 (46.1)
Unable to perform physical activity	6 (7.3)	6 (46.1)
Signs and Symptoms	**n (%)**	**n (%)**
Fever	1 (50.0)	1 (7.7)
Pain	1 (50.0)	1 (7.7)
Side Effects	**n (%)**	**n (%)**
Lose Appetite	6 (13.9)	3 (23.1)
Nausea and Vomiting	3 (7.0)	3 (23.1)
Insomnia	0 (0.0)	0 (0.0)
Diarrhea	2 (4.6)	1 (7.7)
Constipation	5 (11.6)	3 (23.1)
Hair Loss	4 (9.3)	2 (15.4)
Loss of Sensation	5 (11.6)	4 (30.8)
Fatigue (muscle)	13 (30.2)	7 (53.8)
Fatigue (Shortness of Breath)	5 (11.6)	3 (23.1)
Memory Lost	0 (0.0)	0 (0.0)
Surveys	**n (%)**	**n (%)**
Colorectal	6 (35.3)	6 (46.1)
Quality of Life of Cancer Patients	11 (64.7)	6 (46.1)

Colorectal Survey	n (%)	n (%)
Dysuria	2 (13.3)	6 (46.1)
Abdominal pain	4 (26.7)	
Buttock pain	3 (20.0)	
Hair loss	2 (13.3)	
Taste	4 (26.7)	
Quality of Life of Cancer Patients Survey	**n (%)**	**n (%)**
Fatigue	8 (20.5)	6 (46.1)
Nausea and Vomiting	8 (20.5)	
Pain	5 (12.8)	
Insomnia	3 (7.7)	
Appetite Loss	4 (10.3)	
Constipation	8 (20.5)	
Diarrhea	3 (7.7)	

Source: elaborated by the authors.

Table 16 presents the analysis of signs, symptoms, and adverse effects reported by patients in the control and intervention groups. Data from the control group were extracted from the patient's medical records, and from the intervention group were obtained from the patient's self-report. According to the symptoms and adverse effects reported by the patient in the intervention group, the system evaluates the criticality based on pre-established criteria between the project team and the Cecans clinic specialists.

Table 16: Analysis of signs, symptoms, and adverse effects reported by patients in the control and intervention groups. Data from the control group were extracted from the patient's medical records and the intervention group based on the patient's self-report.

Variable	Control	Intervention (self-report)	Total	*p*
Signs and Symptoms / Side Effects	**n (%)**	**n (%)**	**n (%)**	
Yes	11 (64.7)	12 (92.3)	23 (76.7)	0.1038
No	6 (35.3)	1 (7.7)	7 (23.3)	
Fatigue	**n (%)**	**n (%)**	**n (%)**	
Yes	1 (5.9)	12 (92.3)	13 (43.3)	<0.0001*
No	16 (94.1)	1 (7.7)	17 (56.7)	
Appetite Loss	**n (%)**	**n (%)**	**n (%)**	
Yes	0 (0.0)	4 (30.8)	4 (13.3)	0.0261*
No	17 (100.0)	9 (69.2)	26 (86.7)	
Peripheral Neuropathy	**n (%)**	**n (%)**	**n (%)**	
Yes	0 (0.0)	6 (46.2)	6 (20.0)	0.0029*
No	17 (100.0)	7 (53.8)	24 (80.0)	
Hair Loss	**n (%)**	**n (%)**	**n (%)**	

Yes	0 (0.0)	3 (23.1)	3 (10.0)	0.0704
No	17 (100.0)	10 (76.9)	27 (90.0)	
Nausea/Vomiting	**n (%)**	**n (%)**	**n (%)**	
Yes	6 (35.3)	7 (53.8)	13 (43.3)	0.4601
No	11 (64.7)	6 (46.2)	17 (56.7)	
Fever	**n (%)**	**n (%)**	**n (%)**	
Yes	1 (5.9)	1 (7.7)	2 (6.7)	>0.9999
No	16 (94.1)	12 (92.3)	28 (93.3)	
Pain	**n (%)**	**n (%)**	**n (%)**	
Yes	1 (5.9)	8 (61.5)	9 (30.0)	0.0016*
No	16 (94.1)	5 (38.5)	21 (70.0)	
Insomnia	**n (%)**	**n (%)**	**n (%)**	
Yes	1 (5.9)	3 (23.1)	4 (13.3)	0.2903
No	16 (94.1)	10 (76.9)	26 (86.7)	
Diarrhea	**n (%)**	**n (%)**	**n (%)**	
Yes	5 (29.4)	2 (15.4)	7 (23.3)	0.4268
No	12 (70.6)	11 (84.6)	23 (76.7)	
Constipation	**n (%)**	**n (%)**	**n (%)**	
Yes	3 (17.6)	7 (53.8)	10 (33.3)	0.0562
No	14 (82.4)	6 (46.2)	20 (66.7)	

Results are expressed as the number of individuals and percentage (n (%)). Statistical analysis: Fisher test. *p<0.05. Source: elaborated by the authors.

In all, 12 notifications were generated, 3 (25.0%) related to nausea and vomiting, 2 (16.7%) related to diarrhea, 1 (8.3%) related to loss of sensitivity (peripheral neuropathy), 5 (41.7%) related to muscle fatigue and 1 (8.3%) related to fatigue due to shortness of breath, as seen in Table 17. After each notification, the Cecans team contacted the patient to assess their clinical condition and guide them on how to proceed.

Table 17: Notifications generated from the patient's report about their clinical condition.

Variable	Total Notifications
Side Effects	**n (%)**
Nausea and Vomiting	3 (25.0)
Diarrhea	2 (16.7)
Loss of Sensation	1 (8.3)
Fatigue (muscle)	5 (41.7)
Fatigue (shortness of breath)	1 (8.3%)

Source: elaborated by the authors.

6.2.1.6 Analysis of the patient's interaction with the Model and Application of the Face-to-face Survey

Table 18 presents the analysis of signs, symptoms, and adverse effects reported by patients in the intervention group. Data from the intervention group were extracted based on the patient's self-report during the research and based on the application of the face-to-face survey by the researcher on the day of the chemotherapy session. In the face-to-face survey and self-report within the model, most patients reported experiencing fatigue, nausea/vomiting, pain, and constipation at least once during their participation. However, most patients did not experience appetite loss and diarrhea. In the face-to-face survey, most patients reported hair loss and insomnia. Statistical difference in reported hair loss was observed.

Table 18: Analysis of signs, symptoms and adverse effects reported by patients in the intervention group. Data from the intervention group were extracted based on the patient's self-report during the research and based on the application of the face-to-face survey by the researcher on the day of the chemotherapy session.

Variable	Intervention (face-to-face survey)	Intervention (self-report)	*p*
Signs and Symptoms / Side Effects	**n (%)**	**n (%)**	
Yes	13 (100.0)	12 (92.3)	>0.9999
No	0 (0.0)	1 (7.7)	
Fatigue	**n (%)**	**n (%)**	
Yes	13 (100.0)	12 (92.3)	>0.9999
No	0 (0.0)	1 (7.7)	
Appetite Loss	**n (%)**	**n (%)**	
Yes	6 (46.2)	4 (30.8)	0.6882
No	7 (53.8)	9 (69.2)	
Hair Loss	**n (%)**	**n (%)**	
Yes	9 (69.2)	3 (23.1)	0.0472*
No	4 (30.8)	10 (76.9)	
Nausea/Vomiting	**n (%)**	**n (%)**	
Yes	11 (84.6)	7 (53.8)	0.2016
No	2 (15.4)	6 (46.2)	
Pain	**n (%)**	**n (%)**	
Yes	11 (84.6)	8 (61.5)	0.3783
No	2 (15.4)	5 (38.5)	
Insomnia	**n (%)**	**n (%)**	
Yes	8 (61.5)	3 (23.1)	0.1107
No	5 (38.5)	10 (76.9)	

Diarrhea	n (%)	n (%)	
Yes	4 (30.8)	2 (15.4)	0.6447
No	9 (69.2)	11 (84.6)	
Constipation	**n (%)**	**n (%)**	
Yes	8 (61.5)	7 (53.8)	>0.9999
No	5 (38.5)	6 (46.2)	

Results are expressed as the number of individuals and percentage (n (%)). Statistical analysis: Fisher test. *p<0.05. Source: elaborated by the authors.

Table 19 presents the analysis of signs, symptoms, and adverse effects reported by patients in the control and intervention groups. Data from the control group were extracted from the patient's medical records, and data from the intervention group were extracted based on the patient's self-report during the research and based on the application of the face-to-face survey by the researcher on the day of the chemotherapy session. In the control group, it was identified that a minority of patients reported symptoms against the intervention group. This difference provided a statistical difference in all symptoms and adverse effects except for diarrhea.

Table 20 presents the analysis of signs, symptoms, and adverse effects reported by patients in the control and intervention groups. Data from the control group were extracted from the patients' medical records, and data from the intervention group refer to the consolidation of data from the patients' self-reports and the application of the face-to-face survey by the researcher on the days of the chemotherapy sessions. There was a statistical difference in reporting all symptoms and adverse effects, except for diarrhea, where, in both the control and intervention groups, most patients did not report.

Table 19: Analysis of signs, symptoms and adverse effects reported by patients in the control and intervention groups. Data from the control group were extracted from the patient's medical records, and data from the intervention group were extracted based on the patient's self-report during the research and based on the application of the face-to-face survey by the researcher on the day of the chemotherapy session.

Variable	Control	Intervention (face-to-face survey)	Intervention (self-report)	*p*
Signs and Symptoms / Side Effects	**n (%)**	**n (%)**	**n (%)**	
Yes	11 (64.7)	13 (100.0)	12 (92.3)	0.0208*
No	6 (35.3)	0 (0.0)	1 (7.7)	
Fatigue	**n (%)**	**n (%)**	**n (%)**	
Yes	1 (5.9)	13 (100.0)	12 (92.3)	<0.0001*
No	16 (94.1)	0 (0.0)	1 (7.7)	
Appetite Loss	**n (%)**	**n (%)**	**n (%)**	
Yes	0 (0.0)	6 (46.2)	4 (30.8)	0.0092*
No	17 (100.0)	7 (53.8)	9 (69.2)	

Hair Loss	**n (%)**	**n (%)**	**n (%)**	
Yes	0 (0.0)	9 (69.2)	3 (23.1)	0.0001*
No	17 (100.0)	4 (30.8)	10 (76.9)	
Nausea/Vomiting	**n (%)**	**n (%)**	**n (%)**	
Yes	6 (35.3)	11 (84.6)	7 (53.8)	0.0260*
No	11 (64.7)	2 (15.4)	6 (46.2)	
Pain	**n (%)**	**n (%)**	**n (%)**	
Yes	1 (5.9)	11 (84.6)	8 (61.5)	<0.0001*
No	16 (94.1)	2 (15.4)	5 (38.5)	
Insomnia	**n (%)**	**n (%)**	**n (%)**	
Yes	1 (5.9)	8 (61.5)	3 (23.1)	0.0031*
No	16 (94.1)	5 (38.5)	10 (76.9)	
Diarrhea	**n (%)**	**n (%)**	**n (%)**	
Yes	5 (29.4)	4 (30.8)	2 (15.4)	0.5991
No	12 (70.6)	9 (69.2)	11 (84.6)	
Constipation	**n (%)**	**n (%)**	**n (%)**	
Yes	3 (17.6)	8 (61.5)	7 (53.8)	0.0313*
No	14 (82.4)	5 (38.5)	6 (46.2)	

Results are expressed as the number of individuals and percentage (n (%)). Statistical analysis: Chi-square test. *p<0.05. Source: elaborated by the authors.

Table 20: Analysis of signs, symptoms and adverse effects reported by patients in the control and intervention groups. Data from the control group were extracted from the patients' medical records and data from the intervention group refer to the consolidation of data from the patients' self-reports and the application of the face-to-face survey by the researcher on the days of the chemotherapy sessions.

Variable	**Control**	**Intervention (self-report / face-to-face)**	**Total**	***p***
Signs and Symptoms / Side Effects	**n (%)**	**n (%)**	**n (%)**	
Yes	11 (64.7)	13 (100.0)	24 (80.0)	0.0237*
No	6 (35.3)	0 (0.0)	6 (20.0)	
Fatigue	**n (%)**	**n (%)**	**n (%)**	
Yes	1 (5.9)	13 (100.0)	14 (46.7)	<0.0001*
No	16 (94.1)	0 (0.0)	16 (53.3)	
Appetite Loss	**n (%)**	**n (%)**	**n (%)**	
Yes	0 (0.0)	7 (53.8)	7 (23.3)	0.0008*
No	17 (100.0)	6 (46.2)	23 (76.7)	
Hair Loss	**n (%)**	**n (%)**	**n (%)**	
Yes	0 (0.0)	9 (69.2)	9 (30.0)	<0.0001*
No	17 (100.0)	4 (30.8)	21 (70.0)	
Nausea/Vomiting	**n (%)**	**n (%)**	**n (%)**	
Yes	6 (35.3)	11 (84.6)	17 (56.7)	0.0105*

No	11 (64.7)	2 (15.4)	13 (43.3)	
Pain	**n (%)**	**n (%)**	**n (%)**	
Yes	1 (5.9)	12 (92.3)	13 (43.3)	<0.0001*
No	16 (94.1)	1 (7.7)	17 (56.7)	
Insomnia	**n (%)**	**n (%)**	**n (%)**	
Yes	1 (5.9)	9 (69.2)	10 (33.3)	0.0004*
No	16 (94.1)	4 (30.8)	20 (66.7)	
Diarrhea	**n (%)**	**n (%)**	**n (%)**	
Yes	5 (29.4)	5 (38.5)	10 (33.3)	0.7055
No	12 (70.6)	8 (61.5)	20 (66.7)	
Constipation	**n (%)**	**n (%)**	**n (%)**	
Yes	3 (17.6)	10 (76.9)	13 (43.3)	0.0024*
No	14 (82.4)	3 (23.1)	17 (56.7)	

Results are expressed as the number of individuals and percentage (n (%)). Statistical analysis: Fisher test. *p<0.05. Source: elaborated by the authors.

6.2.1.7 User Experience Questionnaire (UEQ) and System Usability Scale (SUS) Surveys

Patients were invited to evaluate the usability and their experience with the proposed new model for monitoring cancer patients. Most patients (7/13; 53.8%) answered surveys about user experience (UEQ) and usability (SUS).

6.2.1.7.1 User Experience Questionnaire

The UEQ offers a benchmark containing consolidated data from 21,175 participants from 468 studies concerning different products (KIM et al., 2023). This study' attractiveness and efficiency scales were rated at 1.95 and 2.14, scores considered excellent when compared to the benchmark, as seen in Figure 38. The perspicuity, dependability, and stimulation scales were rated at 1.96, 1.64, and 1.68. Scores are considered good when compared to the benchmark. The novelty scale was rated at 0.43, with below-average scores compared to the benchmark. A value in the excellent category means the evaluated model is among the best 10% of benchmark results; the good category means 10% of results in the benchmark are better than the evaluated model, 75% of the results are worse; below average means 50% of the results in the benchmark are better than the evaluated model, 25% of the results are worse (MOCHAMMAD ALDI KUSHENDRIAWAN et al., 2021; SCHREPP et al., 2017).

Figure 38: Model scores compared to the UEQ benchmark.

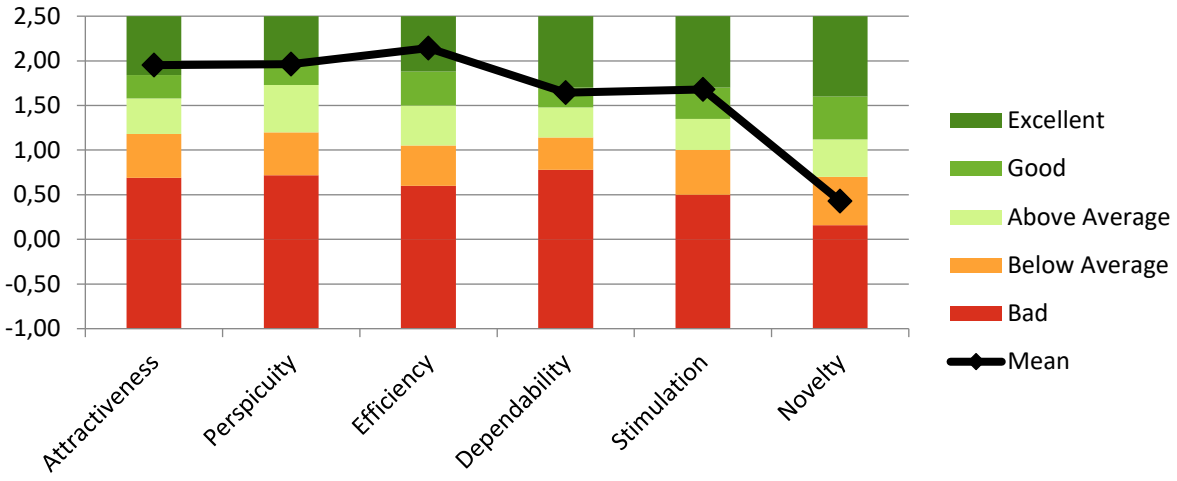


Figure 39 represents the mean and the confidence interval per scale. The range of the scales is between -3 and +3 (DENECKE; VAAHEESAN; ARULNATHAN, 2021). Scale values above 0.8 represent a positive evaluation, values between -0.8 and +0.8 represent a neutral evaluation, and values below -0.8 represent a negative evaluation. The mean of attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty scales was evaluated at 1.95 (variance 0.30), 1.96 (variance 0.32), 2.14 (variance 0.75), 1.64 (variance 0.91), 1.68 (variance 0.62) and 0.43 (variance 1.04), respectively.

Figure 40 represents the distributions of responses in the UEQ by item. The questionnaire comprises 26 items, and each UEQ item consists of a pair of terms with opposite meanings (DENECKE et al., 2021). Users must express their evaluation of each item on a 7-point Likert scale, ranging from 1 (strongly agree with the negative term) to 7 (strongly agree with the positive term); 4 is considered neutral (DENECKE et al., 2021).

Figure 39: The mean and the confidence interval per scale.

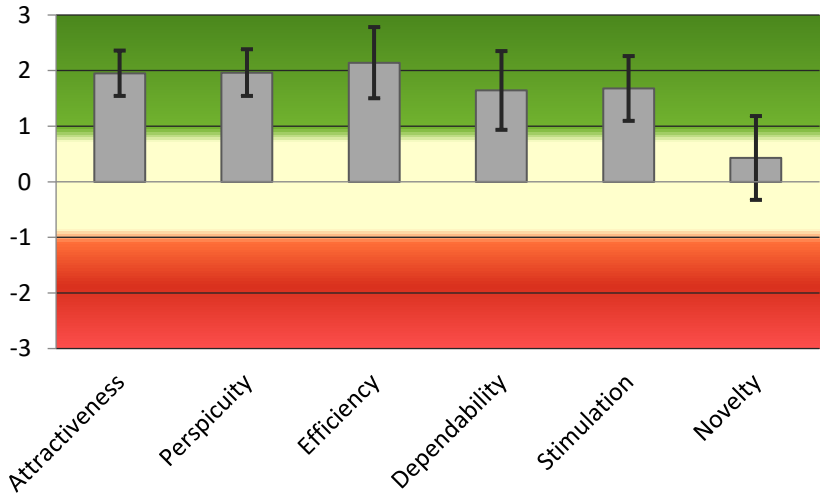
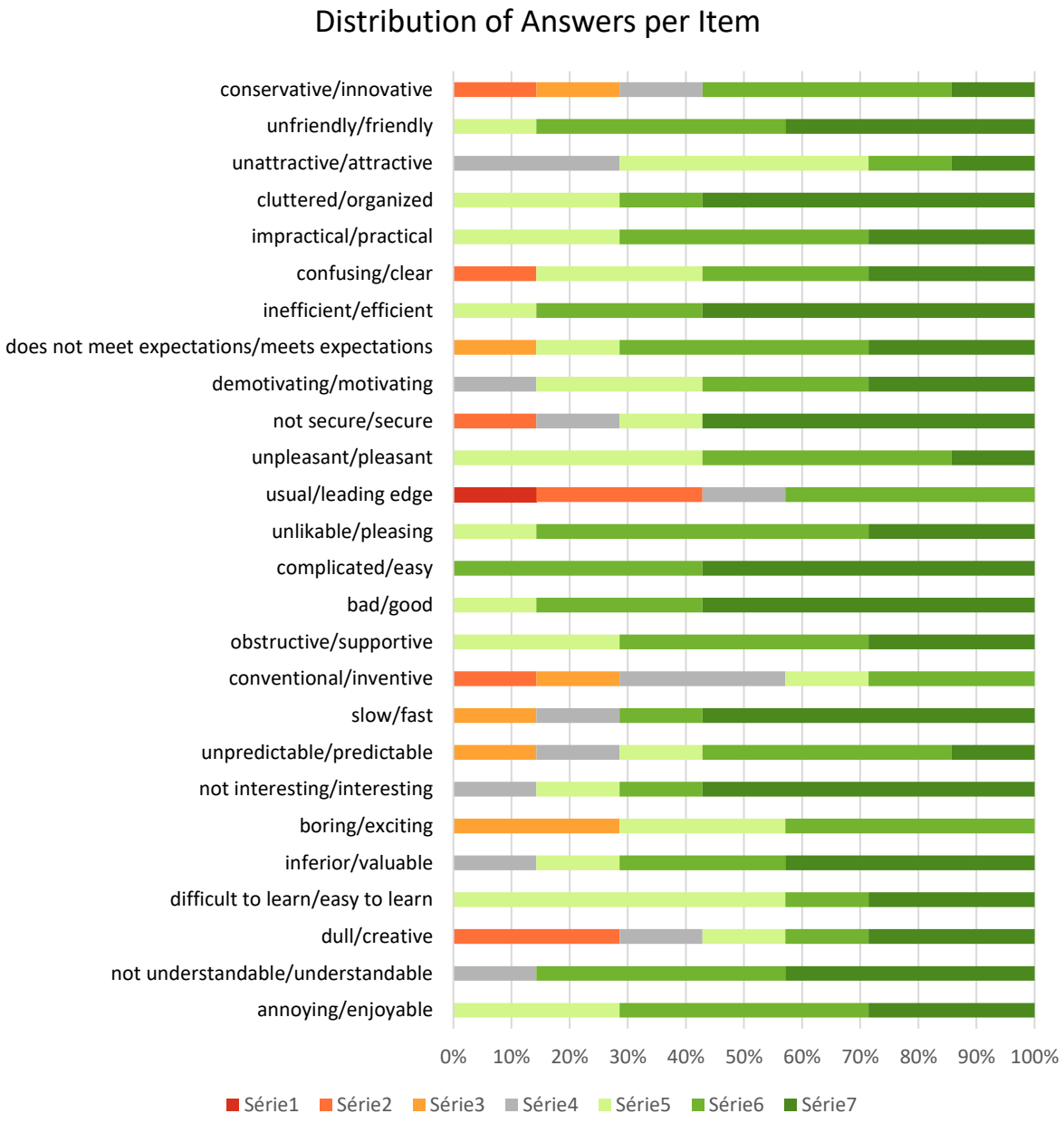


Figure 40: Distribution of Answers per Item.



6.2.1.7.2 System Usability Scale

Patients assessed usability through the SUS. The mean SUS score was 79,6 ± 8.8, and the median was 82.5 (71.3-85.0), as seen in Table 21. Table 21 shows each statement evaluated mean, standard deviation, median, and interquartile range. The minimum and maximum values in this analysis are 0 and 4, respectively. The mean of most comments was above 3 (8/10, 80%), 80% (8/10) had a median of 3, and 90% (9/10) of statements had 75% (interquartile) of their ratings equal to or above 3. Most of the items evaluated had a mean and median similar to or

greater than 3. The evaluation score was normalized, where 0 and 4 mean a negative and positive evaluation of each survey statement, respectively.

Table 21: Responses to individual system usability statements.

Statement		Mean	Standard Deviation	Median	Interquartile Range
1.	I think that I would like to use this chatbot frequently	2.29	0.76	2.00	1 (2 to 3)
2.	I found the chatbot unnecessarily complex	3.00	1.00	3.00	0.5 (3 to 3.5)
3.	I thought the chatbot was easy to use	3.57	0.53	4.00	1 (3 to 4)
4.	I think that I would need the support of a technical person to be able to use this chatbot	3.43	0.53	3.00	1 (3 to 4)
5.	I found that the various functions in this chatbot were well integrated	3.14	0.38	3.00	0 (3 to 3)
6.	I thought that there was too much inconsistency in this chatbot	3.29	0.49	3.00	0.5 (3 to 3.5)
7.	I imagine that most people would learn to use this chatbot very quickly	3.14	0.69	3.00	0.5 (3 to 3.5)
8.	I found the chatbot very cumbersome / awkward to use	3.43	0.53	3.00	1 (3 to 4)
9.	I felt very confident using the chatbot	3.29	0.49	3.00	0.5 (3 to 3.5)
10.	I needed to learn a lot of things before I could get going with this chatbot	3.29	0.49	3.00	0.5 (3 to 3.5)

Source: elaborated by the authors.

6.2.1.8 Evaluation of eating habits and practice of physical activity

The meals most consumed by patients before the intervention were breakfast (84.6%), lunch (92.3%), and dinner (100.0%), as seen in Table 22. Moreover, a minority of patients self-reported consuming morning snacks (38.5%) and afternoon snacks (46.2%), and supper (7.7%). After the intervention, it was observed, based on the patient's self-report, higher consumption of breakfast (92.3%), morning snack (46.2%), afternoon snack (69.2%), and lunch (100%). The amount of water consumed before or after the intervention was very similar. No statistical differences were identified. However, a statistical decrease in alcohol consumption (p=0.0472) was observed. Before the intervention, most patients self-reported alcohol consumption (76.9%), and after the intervention, only 30.8% reported alcohol consumption.

Table 23 shows that before the intervention, most patients self-reported consumption of fruits (69.2%), vegetables (92.3%), and grains (84.6%). Most reported eating one or less fruit daily (53.8%) and two or more tablespoons of grains daily (61.5%). Moreover, after the intervention, there was a statistical increase in fruit consumption (p=0.0297), where 100% self-

reported fruit consumption. Most reported eating two or more fruits a day (61.6%), eating vegetables (84.6%), and grains (92.3%).

Table 22: Analysis of the regular consumption of each type of meal, the daily number of glasses of water, and the frequency of alcoholic beverages. Data were extracted before and after the intervention.

Variable	Before the intervention	After the intervention	*p*
n (%)	**13 (100.0 %)**	**13 (100.0)**	
Breakfast#	**n (%)**	**n (%)**	
Yes	11 (84.6)	12 (92.3)	>0.9999
No	2 (15.4)	1 (7.7)	
Morning snack#	**n (%)**	**n (%)**	
Yes	5 (38.5)	6 (46.2)	>0.9999
No	8 (61.5)	7 (53.8)	
Lunch#	**n (%)**	**n (%)**	
Yes	12 (92.3)	13 (100)	>0.9999
No	1 (7.7)	0 (0.0)	
Afternoon Snack#	**n (%)**	**n (%)**	
Yes	6 (46.2)	9 (69.2)	0.4283
No	7 (53.8)	4 (30.8)	
Dinner#	**n (%)**	**n (%)**	
Yes	13 (100.00)	13 (100.0)	>0.9999
No	0 (0.0)	0 (0.0)	
Supper#	**n (%)**	**n (%)**	
Yes	1 (7.7)	0 (0.0)	>0.9999
No	12 (92.3)	13 (100.0)	
Water (cups/day)	**n (%)**	**n (%)**	
< 4	1 (7.7)	1 (7.7)	0.9684
4 to 5	4 (30.8)	3 (23.1)	
6 to 8	4 (30.8)	4 (30.8)	
≥ 8	4 (30.8)	5 (38.5)	
Alcoholic beverage#	**n (%)**	**n (%)**	
Yes	10 (76.9)	4 (30.8)	0.0472*
No	3 (23.1)	9 (69.2)	
Alcoholic beverage	**n (%)**	**n (%)**	
Non-consumption	3 (23.1)	9 (69.2)	0.0458*
Occasionally	5 (38.5)	3 (23.1)	
Weekly/Daily	5 (38.5)	1 (7.7)	

Results are expressed as the number of individuals and percentage (n (%)). Statistical analysis: Chi-square test and #Fisher test. *p<0.05. Source: elaborated by the authors.

Table 24 shows that, before and after the intervention, most patients self-reported consuming pasta, carbohydrates, cereals (before and after: 100%), and bread (before and after: 76.9%). Furthermore, before the intervention, 38.5% reported rarely consuming sweets and sugary drinks, and 23.1% reported rarely consuming fast food, sausages, and fried food.

However, after the intervention, most patients reported rarely consuming fast food, sausages, and fried food (61.5%).

Table 23: Analysis of patients' behavior before and after the intervention regarding consuming fruits, vegetables, and grains.

Variable	Before the intervention	After the intervention	*p*
n (%)	**13 (100.0 %)**	**13 (100.0)**	
Fruits[#]	**n (%)**	**n (%)**	
Yes	9 (69.2)	13 (100.0)	0.0297*
No	4 (30.8)	0 (0.0)	
Fruits (unit/slice/glass of natural juice)/day	**n (%)**	**n (%)**	
≤ 1	7 (53.8)	5 (38.5)	0.7338
2	3 (23.1)	4 (30.8)	
≥ 3	3 (23.1)	4 (30.8)	
Vegetables[#]	**n (%)**	**n (%)**	
Yes	12 (92.3)	11 (84.6)	>0.9999
No	1 (7.7)	2 (15.4)	
Vegetables (tablespoons/day)	**n (%)**	**n (%)**	
≤ 3	5 (38.5)	5 (38.5)	0.6198
4 to 5	4 (30.8)	5 (38.5)	
6 to 7	4 (30.8)	2 (15.4)	
≥ 8	0 (0.0)	1 (7.7)	
Grain Consumption[#]	**n (%)**	**n (%)**	
Yes	11 (84.6)	12 (92.3)	>0.9999
No	2 (15.4)	1 (7.7)	
Grains (tablespoons/day)	**n (%)**	**n (%)**	
Non-consumption	2 (15.4)	1 (7.7)	0.8810
< 5 times a week	1 (7.7)	2 (15.4)	
≤ 1 tablespoon/day	2 (15.4)	2 (15.4)	
≥ 2 tablespoons/day	8 (61.5)	8 (61.5)	

Results are expressed in number of individuals and percentage (n (%)). Statistical analysis: chi-square test (X^2) and [#]Fisher test. *p<0.05. Source: elaborated by the authors.

Most patients self-reported consuming meat or eggs (before: 100.0%; after: 92.3%), the most common daily consumption being two meat pieces or eggs (before: 61.5%; after: 53.8%, p=0.5866), as seen in Table 25. Before the intervention, 5 (38.5%) patients self-reported that they usually removed visible fat from the meat. After the intervention, there were 10 (76.9%) patients (p=0.1107). The frequency of fish consumption remained similar before and after the intervention, but there was an increase in the consumption of milk and dairy products (before: 61.5%; after: 84.6%; p=0.3783). Whole milk was the most common type of milk consumed by patients (before: 53.8%; after: 69.2%; p=0.3928). Consumption of meat, fish, dairy products, and milk remained similar before and after the intervention. The habit of removing visible fat

from meat was the only change in animal protein consumption; most patients self-reported that they had this behavior after the intervention.

Table 26 shows the types of activity and the frequency performed by the patients before and after the intervention. Before the intervention, 5 (38.5%) patients self-reported practicing physical activity, with two reporting practicing walking and five reporting practicing other physical activities, such as running, bodybuilding, beach tennis, and pilates. After the intervention, 7 (53.8%) patients reported practicing physical activity, with walking being the most common activity (6/13; 46.1%).

Table 24: Analysis of pasta, carbohydrates, cereals, industrialized beverages, fast food, and sweets consumption by patients before and after the intervention.

Variable	Before the intervention	After the intervention	*p*
n (%)	**13 (100.0 %)**	**13 (100.0)**	
Pasta, carbohydrates, and cereals #	**n (%)**	**n (%)**	
Yes	13 (100)	13 (100.0)	>0.9999
No	0 (0.0)	0 (0.0)	
Pasta, carbohydrates, and cereals (tablespoons/day)&	**3.0 (2.5 – 4.5)**	**4 (3.0 – 5.0)**	**0.8828**
Bread #	**n (%)**	**n (%)**	
Yes	10 (76.9)	10 (76.9)	>0.9999
No	3 (23.1)	3 (23.1)	
Bread (units or slices)/day&	**1.0 (0.5 – 2.0)**	**1.0 (0.5 – 2.0)**	**0.8125**
Simple Cake#	**n (%)**	**n (%)**	
Yes	1 (7.7)	3 (23.1)	0.5930
No	12 (92.3)	10 (76.9)	
Simple cakes (slices/day) &	**0.0 (0.0 - 0.0)**	**0.0 (0.0 – 0.5)**	**>0.9999**
Simple Biscuits#	**n (%)**	**n (%)**	
Yes	4 (30.8)	1 (7.7)	0.3217
No	9 (69.2)	12 (92.3)	
Simple biscuits (units /day) &	**0.0 (0.0 – 2.5)**	**0.0 (0.0 – 0.0)**	**0.4375**
Fast Food and Sausages and Fried Food	**n (%)**	**n (%)**	
Rarely	3 (23.1)	8 (61.5)	0.1588
Daily	1 (7.7)	0 (0.0)	
< 2 times a week	5 (38.5)	4 (30.8)	
2-3 times a week	4 (30.8)	1 (7.7)	
Sweets and Sugary Drinks	**n (%)**	**n (%)**	
Rarely	5 (38.5)	5 (38.5)	0.4801
Daily	1 (7.7)	1 (7.7)	
< 2 times a week	2 (15.4)	5 (38.5)	
2-3 times a week	3 (23.1)	2 (15.4)	
4-5 times a week	2 (15.4)	0 (0.0)	

Results are expressed as median (interquartile of 25% and 75%) or in number of individuals and percentage (n (%)). Statistical analysis: chi-square test (X^2), # Fisher test, and &Wilcoxon test. Source: elaborated by the authors.

Table 25: Analysis of animal protein (meat, fish, milk, and dairy products) consumption by patients before and after the intervention.

Variable	Before the intervention	After the intervention	*p*
n	**13 (100.0 %)**	**13 (100.0)**	
Meats (cattle, pig, poultry, fish and other) or Eggs#	**n (%)**	**n (%)**	
Yes	13 (100.0)	12 (92.3)	>0.9999
No	0 (0.0)	1 (7.7)	
Daily consumption of meat or eggs	**n (%)**	**n (%)**	
Non-consumption	0 (0.0)	1 (7.7)	0.5866
2 pieces or 2 eggs	8 (61.5)	7 (53.8)	
> 2 pieces or 2 eggs	5 (38.5)	5 (38.5)	
Usually remove the apparent fat from the meat?#	**n (%)**	**n (%)**	
Yes	5 (38.5)	10 (76.9)	0.1107
No	8 (61.5)	3 (23.1)	
Type of fat used	**n (%)**	**n (%)**	
Animal lard or butter	3 (23.1)	4 (30.8)	>0.9999
Vegetable oil such as: soybean, corn, or canola	10 (76.9)	9 (69.2)	
Fish#	**n (%)**	**n (%)**	
Yes	13 (100.0)	13 (100.0)	>0.9999
No	0 (0.0)	0 (0.0)	
Frequency of fish consumption	**n (%)**	**n (%)**	
A few times a year	3 (23.1)	3 (23.1)	0.8219
1 to 4 times a month	8 (61.5)	9 (69.2)	
≥ 2 times a week	2 (15.4)	1 (7.7)	
Milk and dairy products#	**n (%)**	**n (%)**	
Yes	8 (61.5)	11 (84.6)	0.3783
No	5 (38.5)	2 (15.4)	
Amount of Milk and dairy products (cups or pieces or slices per day)	**n (%)**	**n (%)**	
Non-consumption	5 (38.5)	2 (15.4)	0.2806
≤ 1 time a day	4 (30.8)	6 (46.2)	
2 times a day	4 (30.8)	3 (23.1)	
≥ 3 times a day	0 (0.0)	2 (15.4)	
Type of milk and derivatives	**n (%)**	**n (%)**	
Non-consumption	5 (38.5)	2 (15.4)	0.3928
Whole milk	7 (53.8)	9 (69.2)	
Low fat (skimmed, semi-skimmed and light milk)	1 (7.7)	2 (15.4)	

Results are expressed in number of individuals and percentage (n (%)). Statistical analysis: chi-square test (X^2), #Fisher test. Source: elaborated by the authors.

Table 27 presents the general score of the questionnaire self-reported by the patients before and after the intervention. From 0 to 28 points, the standard feedback in the questionnaire

is "You need to make your diet and life habits healthier!". From 29 to 42, the feedback is "Be careful with your diet and other habits such as physical activity and fluid consumption.". Finally, 43 points or more, "Congratulations! You're on the way to healthy living.".

Table 26: Distribution of the type and frequency of physical activity the patient performed before and after diagnosis.

Variable	Before the intervention	After the intervention	*p*
n	**13 (100.0 %)**	**13 (100.0)**	
Physical activity practice[#]	**n (%)**	**n (%)**	
Yes	5 (38.5)	7 (53.8)	0.6951
No	8 (61.5)	6 (46.2)	
Type of Physical Activity[#]	**n (%)**	**n (%)**	
Walking	Yes (2) No (11)	Yes (6) No (7)	0.2016
Others (running, bodybuilding, beach tennis, pilates)	Yes (5) No (8)	Yes (2) No (11)	0.3783
Frequency of Physical Activity	**n (%)**	**n (%)**	
No practice	8 (61.5)	6 (46.2)	0.3658
Occasionally	0 (0.0)	2 (15.4)	
Daily	4 (30.8)	3 (23.1)	
2 times a week	1 (7.7)	0 (0.0)	
3 times a week	0 (0.0)	1 (7.7)	
4 times a week	0 (0.0)	1 (7.7)	

Results are expressed in number of individuals and percentage (n (%)). Statistical analysis: chi-square test and [#]Fisher test. Source: elaborated by the authors.

Table 27: Overall score of the Food Guide: how to have a healthy diet questionnaire.

Variable	Before the intervention	After the intervention
n	**13 (100.0 %)**	**13 (100.0)**
Questionnaire Score	**n (%)**	**n (%)**
0 to 28	5 (38.5)	0 (0.0)
29 to 42	8 (61.5)	11 (84.6)
43 to –	0 (0.0)	2 (15.4)

Source: elaborated by the authors.

6.2.2 Discussion

Our results demonstrated the use of the model by 13 patients with colorectal cancer in active treatment. According to our results, it was possible to observe that most patients used the chatbot frequently, increased the practice of physical activity (with or without the use of the wearable device), and reported several adverse effects, including some of the clinical relevance, which generated notifications for the multidisciplinary team, thus contributing to better follow-

up and monitoring of patients. When comparing the control group with the intervention groups, it was observed that the model contributed to greater patient engagement.

No clinical and epidemiological difference was observed between patients in the control and intervention groups, demonstrating that the groups were homogeneous. When comparing age ranges, body mass index (BMI), gender, and staging between groups, no statistical differences were identified. According to epidemiological data, it was observed that the mean BMI was 26.9 and 26.1 in the control and intervention groups, respectively, demonstrating that both groups were overweight. Several studies have shown an increase in overweight people worldwide and have demonstrated that this overweight condition contributes to the development of tumors, including colorectal cancer, with a worst clinical profile (LAZARUS; BAYS, 2022; QUEIROZ; CARNEIRO, et al., 2022).

Furthermore, the results showed that the mean age of both groups was 50 years old, with most patients in both groups aged 45 years or older. However, the percentage of patients aged 25 to 44 years old was relevant in both groups, 41.2% in the control group and 46.6% in the intervention group, indicating an increased cancer incidence in younger people. According to gender, the total number of men was higher than that of women. Studies have been demonstrating that overweight and obese individuals, as well as male individuals, have a greater risk for cancer development (LOOSEN et al., 2022). However, in our study, we could observe that in the intervention group, most were women; this divergence is probably due to the volume of patients considered in the research.

82.4% and 76.9% of patients were stage 3 or 4 in the control and intervention groups, respectively. The most used protocol was mFolfox6 (control: 53.0%; intervention: 76.9%), and the most type of treatment were surgery and chemotherapy associated (control: 82.4%; intervention: 76.9%). In most patients, the cancer was primary (control: 88.2%; intervention: 92.3%), without metastasis (control: 70.6%; intervention: 92.3%), and with affected lymph nodes (control: 58.8%; intervention: 76.9%). The evolution of colorectal cancer usually occurs in a silent and asymptomatic way, contributing to late diagnosis and more advanced staging (QASEEM et al., 2019).

Most patients who reported food intake indicated a reduction in consumption during a treatment period, but in all cases, there was normalization in the following weeks. It is well known that the cancer condition can decrease food intake, and appetite, promoting an anorexic condition (FERIOLI et al., 2018; LAZARUS; BAYS, 2022). Furthermore, antineoplastic drugs

can also reduce the appetite reducing the food intake, which can debilitate the patient (FERIOLI et al., 2018). Thus, these results demonstrate the importance of monitoring and encouraging/guiding patients about food intake.

The most common practice of physical activity identified in the intervention group was walking, practiced by 84.6% (11/13) of patients. The relevance of this activity was expected since it is the physical activity physicians recommend to all patients. Patients are instructed to perform low-impact and light physical activities during chemotherapy to avoid injuries. The other physical activities performed were bodybuilding, beach tennis, and cycling.

In the intervention group, 38.46% (5/13) of patients self-reported that they had practiced any physical activity before the intervention. After participating in the study, all patients performed physical activity for at least 1 week, and 46.15% (6/13) completed it for at least four weeks. In addition, 5 (38.46%) patients self-reported that they practiced regularly and 2 (15.38%) occasionally. In contrast, there was a reduction in the control group from 11 to 5 patients who self-reported physical activity before and after diagnosis, respectively. These results suggest that the model stimulated the practice of physical activity by the patients.

We observed that most patients (61.5%) interacted with the chatbot for at least 5 weeks (62.5%) during participation in the research. During this period, patients actively self-reported signs and symptoms, physical activity data, and completed surveys on quality of life and colorectal cancer. Most patients (61.5%) reported some symptoms or adverse effects during 50% of the weeks. Chatbots can contribute to the development of healthcare by promoting knowledge and guidance to patients (GÖRTZ et al., 2023).

Regarding physical activity, patient engagement was 30.8% with the use of the wearable device and 46.2% regardless of using the smart band in at least half of the weeks of the intervention. In addition, all patients reported practicing physical activity in at least one of the weeks of participation. It was observed that in most weeks, the activity practice in the second week after chemotherapy was equal to or greater than in the first week. This data was expected since the adverse effects usually attenuate in the second week.

In the intervention group, the most common adverse effects reported by patients were fatigue (92.3%), peripheral neuropathy (46.2%), nausea and vomiting (53.8%), pain (61.5%), and constipation (53.8%). In the control group, the most reported adverse effects were nausea and vomiting (35.3%), diarrhea (29.4%), and constipation (17.6%). Statistical differences were identified in reports of adverse effects of fatigue (control: 1 (5.9%), intervention: 12 (92.3%);

$p < 0.0001$), appetite loss (control: 0 (0.0%), intervention: 4 (30.8%); $p = 0.0261$), peripheral neuropathy (control: 0 (0.0%), intervention: 6 (46.2%); $p = 0.0029$) and pain (control: 1 (5.9%), intervention: 8 (61.5%); $p = 0.0016$), comparing control and intervention groups, indicating that patients who participated in the model reported more accurately. Corroborating, Tawfik et al. demonstrated that cancer patients undergoing chemotherapy in the chatbot group presented more effective self-care behavior than those in the routine care group (TAWFIK et al., 2023).

During the follow-up of patients in the intervention group, 12 notifications were generated for the multidisciplinary clinical team based on the patients' self-reports. These notifications allowed the clinic's specialists to proactively contact patients, clarifying doubts and guiding them on the most appropriate conduct. Muscle fatigue was the adverse effect that generated the most reports, followed by nausea and vomiting, and diarrhea. The result corroborates that chatbots can assess the criticality of self-reported symptoms, triggering the multidisciplinary team only in case of deterioration of the clinical condition (GÖRTZ et al., 2023).

Symptoms and adverse effects reported in the face-to-face survey and self-reported in the SMT, both in the intervention group, were similar, except for hair loss and insomnia, indicating that the adverse effects of hair loss and insomnia may not have caused so much discomfort to patients during treatment. Reports from the control group presented statistical differences compared to the intervention group (face-to-face survey and self-report) in most symptoms and adverse effects, suggesting that the model may have contributed to a more accurate report.

Upon intervention completion, patients were asked to respond to the UEQ and the SUS surveys. The model scored high on most UEQ scales. Most scores were above the benchmark and are graphically represented in Figure 38, indicating that users' expectations were addressed. In the mean and the confidence interval per scale (Figure 39), it was observed that most of the scales presented values greater than 1, representing a positive evaluation of the model. Analyzing the distributions of responses in the UEQ per item (Figure 40), the results show that most patients considered the model innovative, friendly, efficient, enjoyable, secure, fast, pleasant, supportive, among others.

We can observe that the novelty scale was the only one with a neutral and below-average evaluation compared to the benchmark. The items creative/dull, inventive/conventional,

usual/leading edge, and conservative/innovative were evaluated in this scale. Most patients (4/7; 57.1%) rated the dull/creative item above 4, indicating that the system is clever; 3 (42.9%) patients evaluated the conventional/inventive item above 4, and 2 (28.6%) rated it as neutral, suggesting a tendency from neutral to inventive; 3 (42.9%) patients rated the usual/leading edge item above 4 and 1 (14.3%) evaluated it as neutral, suggesting a tendency from neutral to the leading edge; 4 (57.1%) patients evaluated the conservative/innovative item above 4 and 1 (14.3%) considered it as neutral, indicating that the system is innovative. Thus, although the novelty scale was characterized as neutral, we can observe that most patients classified their experience with the model as creative and innovative.

Regarding evaluating the system's usability, the mean SUS score was 79,6 ± 8.83. SUS scores above 68 indicate the system has acceptable usability (BANGOR; KORTUM; MILLER, 2008; ISSOM et al., 2021; OH et al., 2020; STARA et al., 2021). Thus, the evaluation suggests that the model addressed patients' expectations regarding usability. Recent studies demonstrate patients' adherence to the use of the chatbot in the healthcare area, as well as good usability rates and positive evaluation of perceived benefits (GÖRTZ et al., 2023; SIGLEN et al., 2022). Our intention for future work is to extend the application of the model to other types of cancer, such as prostate and breast cancer, one of the most common in men and women, respectively, to contribute to patient monitoring and self-management during the active treatment phase.

Patients in the intervention group responded at week 0, the beginning of the intervention, to a survey about their eating habits and practice of physical activity before cancer diagnosis. At week 8, patients answered the same questionnaire focusing on the intervention period. Studies report that one of the adverse effects of treatment with antineoplastic drugs is decreased food intake and lack of appetite, which can lead to anorexia (FERIOLI et al., 2018; LAZARUS; BAYS, 2022). However, our results indicate that patients improve their eating habits by eating more frequently during the day. After the intervention, a statistical decrease in alcohol consumption ($p=0.0472$) was observed. The diagnosis, medical advice, and participation in the study may have contributed to this relevant reduction in consumption. Several studies have shown an association between alcohol consumption and CRC incidence (GHAZALEH DASHTI et al., 2017; THANIKACHALAM; KHAN, 2019).

Moreover, after the intervention, there was a statistical increase in fruit consumption ($p=0.0297$), where 100% self-reported fruit consumption. The application of the questionnaire during the intervention may have contributed to the improvement in fruit consumption, as patients were encouraged to reflect on their current behavior. Fruit consumption is a crucial

factor in primary cancer prevention. Consumption has been associated with a lower mortality rate for cancer survivors (HURTADO-BARROSO et al., 2020).

During the survey, patients self-reported a decrease in fast food consumption, 23.1% self-reported rarely consuming this type of food, and now it is 61.5%. This is essential data since consuming processed meats, such as hamburgers, sausages, and bacon, contributes to increased cancer risk (THANIKACHALAM; KHAN, 2019; WILDE et al., 2019). Red meat consumption is one of the main risk factors for CRC (THANIKACHALAM; KHAN, 2019; WILDE et al., 2019), and the consumption profile of patients before diagnosis may have contributed to the development of cancer. Participation in the intervention did not change the amount of meat consumed.

As expected, walking was the most practiced physical activity after the intervention since the physicians at the clinic advised all patients to prioritize walking, light, and low-impact physical exercise. As a positive result, we had an increase in the practice of physical activity by patients (FERIOLI et al., 2018), even during the active phase of treatment, although no statistical difference was observed. This result suggests that the model stimulated the practice of physical activity by the patients. However, during treatment, patients usually experience various adverse effects due to the antineoplastic drugs administered, which typically contribute to decreased physical exercise.

Patients' scores on the questionnaire indicate an exciting improvement in eating habits before and after the intervention, corroborating that using the new monitoring model may have contributed to a better quality of life for the patient.

6.3 Case Study

In this section, we present the simulation and evaluation of the SMT model integrated into the recommendation system using examples of real interactions that occurred during the prospective clinical study described in 5.3.

6.3.1 Results

Several recommendations were listed for each symptom and adverse effect, which can be used individually or combined with each other, as shown in Table 9. As a suggestion, we

highlight some guidelines within options, as seen in peripheral neuropathy and constipation adverse effects.

Some protocols have adverse effects that affect most patients, which requires the need to guide patients in the first chemotherapy session. In the mFolfox6 and Xelox protocols, it is common for the patient to report peripheral neuropathy, and this adverse effect can be precipitated or exacerbated if the patient does not take some precautions from the beginning of the treatment (HOSPITAL SIRIO-LIBANÊS, 2023).

6.3.1.1 Case Study 1

A patient was recently diagnosed with CRC. The defined protocol was mFolfox6 with 12 chemotherapy sessions. The following recommendations were given to the patient on the day of the first chemotherapy session (Table 28). Users were required to rate each recommendation on a scale of 1 to 5 (1 represents a more negative evaluation, 3 neutral, and 5 is a more positive evaluation).

Table 28: Recommendations in the first chemotherapy session of the first case study.

Recommendations	Rating
• Avoid places with air conditioning (bedrooms, living rooms, among others). When sleeping, bundle up and/or cover up. • Avoid contact with places, objects, and surfaces with ice. Avoid touching the fridge, get ice. Avoid taking things out of the fridge. If necessary, make contact, preferably, with gloves or some type of protection to avoid direct contact. • Tingling or numbness in the hands, feet, legs, and arms, as well as in other parts such as the mouth and ears; weakening or loss of any of the senses, especially touch; and decreased sensitivity, and cramps. These symptoms may be precipitated or exacerbated by exposure to cold temperatures or objects.	4

Between the 1st and 2nd chemotherapy sessions, the patient reported feeling the following symptoms: fatigue (related to weakness/discouragement), nausea, loss of appetite, and constipation (Table 29).

Table 29: Recommendations between the first and second chemotherapy sessions of the first case study.

Symptoms/Adverse Effects	Recommendations	Rating
Nausea/vomiting	• It is recommended to consume foods that are slightly drier and slightly more acidic, which can help reduce salivation and reduce the bitter taste in the mouth. It is usually this feeling of dry mouth and bitter taste in the mouth that contributes to nausea.	4
	• Examples of slightly more acidic foods: pineapple, kiwi, lemon juice, and Gatorade.	5
Constipation	• It is recommended to drink a lot of water, a lot of fluids in general (at least 1.5-2 liters a day).	3

	• Regular consumption of fiber is indicated, such as oatmeal, oat flakes, and fiber-rich fruits (for example: papaya, beetroot, okra, fresh or dried plums, apples, pears, and unpeeled peaches).	4
	• It is recommended to use Tamarine in syrup, capsule, or jelly, following your doctor's instructions. It is a natural product and is usually found in pharmacies or health food stores.	5
Fatigue	• It is recommended to practice physical activity, for example, walking, at least 3 times a week for a period of 20 to 30 minutes, which can help you to improve fatigue (weakness). Physical activity should be light and of low impact during the treatment period.	3
Lose appetite	• It is recommended to prioritize the consumption of food more frequently during the day and in small quantities. It is indicated to consume what you like and give you pleasure, the important thing is to eat.	2
	• Usually, during this period, the consumption of lighter, pastier, and more liquid and easy to swallow foods, such as soups and broths, is indicated, however, consume what best pleases your palate.	5

Between the 2nd and 3rd chemotherapy sessions, the patient reported loss of appetite, fatigue, nausea, pain (intensity 2), and constipation (Table 30).

Table 30: Recommendations between the second and third chemotherapy sessions of the first case study.

Symptoms/Adverse Effects	Recommendations	Rating
Nausea/vomiting	• It is recommended not to spend a long time without eating, try to eat in a shorter time interval between meals.	5
	• Examples of slightly more acidic foods: pineapple, kiwi, lemon juice, and Gatorade.	5
	• In the Mfolfox6 and Xelox protocols, cold fruits, drinks, and foods are not suitable due to the sensitivity that the medication can also cause in the throat.	5
Constipation	• It is recommended to consume a portion (teaspoon) of coconut oil. It can be purchased in markets or natural products stores.	5
	• Here are some behavioral guidelines: o Discipline the appearance of the reflex with the condition of doing it every day, that is, whenever you have a chance to poop, do it, preferably, at the same time every day. Reflex conditioning is present after 2-3 weeks of training. o Dedicate all your attention, without distractions. o Adopt a sitting posture, with the support of the lower limbs on the floor, working as a lever, and flexing the trunk over the abdomen, avoiding the reclining attitude. o Increased physical activity is accompanied by greater regularity of defecation, that is, physical activity helps you to poop (evacuate) more regularly.	4
Fatigue	• It is recommended to practice a hobby or an activity that gives you pleasure, for example, walking, taking a walk in the park, listening to music, reading a book, watching a movie, going out with family, and meeting friends. Seek to perform an activity that gives you satisfaction.	2

Pain	• The recommendation is to continue taking the medications as recommended by the doctor (continue monitoring). If you are unable to take your pain medication, it is recommended that you contact your doctor as soon as possible.	3
Lose appetite	• It is recommended to eat small portions every 2 hours. This will help you to be able to eat better.	4

Between the 3rd and 4th chemotherapy session, the patient reported hair loss, fatigue, nausea, and constipation (Table 31).

Table 31: Recommendations between the third and fourth chemotherapy sessions of the first case study.

Symptoms/Adverse Effects	Recommendations	Rating
Nausea/vomiting	• It is recommended to consume foods that are slightly drier and slightly more acidic, which can help reduce salivation and reduce the bitter taste in the mouth. It is usually this feeling of dry mouth and bitter taste in the mouth that contributes to nausea.	5
Constipation	• Regular consumption of fiber is indicated, such as oatmeal, oat flakes, and fiber-rich fruits (for example: papaya, beetroot, okra, fresh or dried plums, apples, pears, and unpeeled peaches).	5
	• It is recommended to use Tamarine in syrup, capsule, or jelly, following your doctor's instructions. It is a natural product and is usually found in pharmacies or health food stores.	5
	• It is recommended to consume a portion (teaspoon) of coconut oil. It can be purchased in markets or natural products stores.	5
Hair loss	• It is recommended not to wash your hair every day. Avoid washing your hair too often. Avoid brushing your hair several times a day. Some attitudes will help ease the period of hair loss, but there is no way to prevent hair loss.	4
Fatigue	• It is recommended to practice physical activity, for example, walking, at least 3 times a week for a period of 20 to 30 minutes, which can help you to improve fatigue (weakness). Physical activity should be light and of low impact during the treatment period.	3

Between the 4th and 5th chemotherapy sessions, the patient reported loss of sensitivity (tingling in the hands and feet and cold hands), pain (intensity 2), and hair loss (Table 32).

Table 32: Recommendations between the fourth and fifth chemotherapy sessions of the first case study.

Symptoms/Adverse Effects	Recommendations	Rating
Peripheral neuropathy	• During this protocol, it is recommended to avoid contact with cold surfaces/objects/food/environments even when you are not feeling very sensitive so that this adverse effect can be mitigated or postponed. The more tactful you are, the more stimulus sensitivity can be generated.	4
	• Have a fabric glove in the kitchen (usually in the place where you have more contact with cold surfaces or objects), and avoid going barefoot (try to always wear tighter socks or shoes), especially when you feel more sensitive.	5
Hair loss	• Unfortunately, it is not possible to stop hair loss, however, to reduce hair loss, it is recommended to avoid washing your hair too often	5

	and use a brush moderately. If you feel more comfortable, you can cut your hair a little or adopt a scarf.	
Pain	• The recommendation is to continue taking the medications as recommended by the doctor (continue monitoring). If you are unable to take your pain medication, it is recommended that you contact your doctor as soon as possible.	3

6.3.1.2 Case Study 2

A patient was recently diagnosed with colorectal cancer. The defined protocol was mFolfox6 with 12 chemotherapy sessions. On the day of the first chemotherapy session, the following recommendations were given to the patient (Table 33):

Table 33: Recommendations in the first chemotherapy session of the second case study.

Recommendations	Rating
• Avoid places with air conditioning (bedrooms, living rooms, among others). When sleeping, bundle up and/or cover up. • Avoid contact with places, objects, and surfaces with ice. Avoid touching the fridge, get ice. Avoid taking things out of the fridge. If necessary, make contact, preferably, with gloves or some type of protection to avoid direct contact. • Tingling or numbness in the hands, feet, legs, and arms, as well as in other parts such as the mouth and ears; weakening or loss of any of the senses, especially touch; and decreased sensitivity, and cramps. These symptoms may be precipitated or exacerbated by exposure to cold temperatures or objects.	5

The patient reported nausea between the 1st and 2nd chemotherapy sessions (Table 34).

Table 34: Recommendations between the first and second chemotherapy sessions of the second case study.

Symptoms/Adverse Effects	Recommendations	Rating
Nausea/vomiting	• It is recommended to consume foods that are slightly drier and slightly more acidic, which can help reduce salivation and reduce the bitter taste in the mouth. It is usually this feeling of dry mouth and bitter taste in the mouth that contributes to nausea.	5
	• Examples of slightly more acidic foods: pineapple, kiwi, lemon juice, and Gatorade.	5

Between the 2nd and 3rd chemotherapy sessions, the patient reported fatigue, nausea, loss of appetite, and constipation (Table 35).

Table 35: Recommendations between the second and third chemotherapy sessions of the second case study.

Symptoms/Adverse Effects	Recommendations	Rating
Nausea/vomiting	• In the Mfolfox6 and Xelox protocols, cold fruits, drinks, and foods are not suitable due to the sensitivity that the medication can also cause in the throat.	5
	• Examples of slightly more acidic foods: pineapple, kiwi, lemon juice, and Gatorade.	4

Constipation	• Regular consumption of fiber is indicated, such as oatmeal, oat flakes, and fiber-rich fruits (for example: papaya, beetroot, okra, fresh or dried plums, apples, pears, and unpeeled peaches).	3
	• It is recommended to use Tamarine in syrup, capsule, or jelly, following your doctor's instructions. It is a natural product and is usually found in pharmacies or health food stores.	5
	• It is recommended to consume a portion (teaspoon) of coconut oil. It can be purchased in markets or natural products stores.	4
Fatigue	• It is recommended to practice physical activity, for example, walking, at least 3 times a week for a period of 20 to 30 minutes, which can help you to improve fatigue (weakness). Physical activity should be light and of low impact during the treatment period.	5
Lose appetite	• Usually, during this period, the consumption of lighter, pastier, and more liquid and easy to swallow foods, such as soups and broths, is indicated, however, consume what best pleases your palate.	5
	• It is recommended to eat small portions every 2 hours. This will help you to be able to eat better.	4

Between the 3rd and 4th chemotherapy sessions, the patient reported fatigue, nausea, insomnia, loss of appetite, and constipation (Table 36).

Table 36: Recommendations between the third and fourth chemotherapy sessions of the second case study.

Symptoms/Adverse Effects	Recommendations	Rating
Nausea/vomiting	• In its protocol, it is not recommended to consume cold foods due to the sensitivity that can be generated by the medication.	4
	• It is recommended to consume foods that are slightly drier and slightly more acidic, which can help reduce salivation and reduce the bitter taste in the mouth. It is usually this feeling of dry mouth and bitter taste in the mouth that contributes to nausea.	5
Constipation	• Here are some behavioral guidelines: o Discipline the appearance of the reflex with the condition of doing it every day, that is, whenever you have a chance to poop, do it, preferably, at the same time every day. Reflex conditioning is present after 2-3 weeks of training. o Dedicate all your attention, without distractions. o Adopt a sitting posture, with the support of the lower limbs on the floor, working as a lever, and flexing the trunk over the abdomen, avoiding the reclining attitude. o Increased physical activity is accompanied by greater regularity of defecation, that is, physical activity helps you to poop (evacuate) more regularly.	5
Fatigue	• It is recommended to practice a hobby or an activity that gives you pleasure, for example, walking, taking a walk in the park, listening to music, reading a book, watching a movie, going out with family, and meeting friends. Seek to perform an activity that gives you satisfaction.	3
Insomnia	• Here are some important tips that can help you get a good night's sleep:	5

	○ Get up every day at the same time and maintain a sleep routine; ○ Limit the amount of time lying in bed before sleep; ○ Limit or suspend psychotropic substances (alcohol, caffeine, stimulants, among others); ○ Avoid sleeping during the day; ○ Physical activity: perform in the morning and avoid practicing for about four hours before bedtime; ○ Avoid stimulating activities at night: TV, cell phone, and social networks; ○ Avoid heavy evening meals; ○ Keep a room suitable for sleep: reduce stimuli such as light and sound; ○ Avoid screens before or at bedtime (computers, phones, tablets, e-books); ○ Solve problems before bedtime; ○ Do not force sleep; ○ Meditate or perform relaxation techniques.	
Lose appetite	• It is recommended to prioritize the consumption of food more frequently during the day and in small quantities. It is indicated to consume what you like and give you pleasure, the important thing is to eat.	4

Between the 4th and 5th chemotherapy sessions, the patient reported loss of sensitivity (tingling in the hands and feet, and cold in the hands), pain (intensity 2), and hair loss (Table 37).

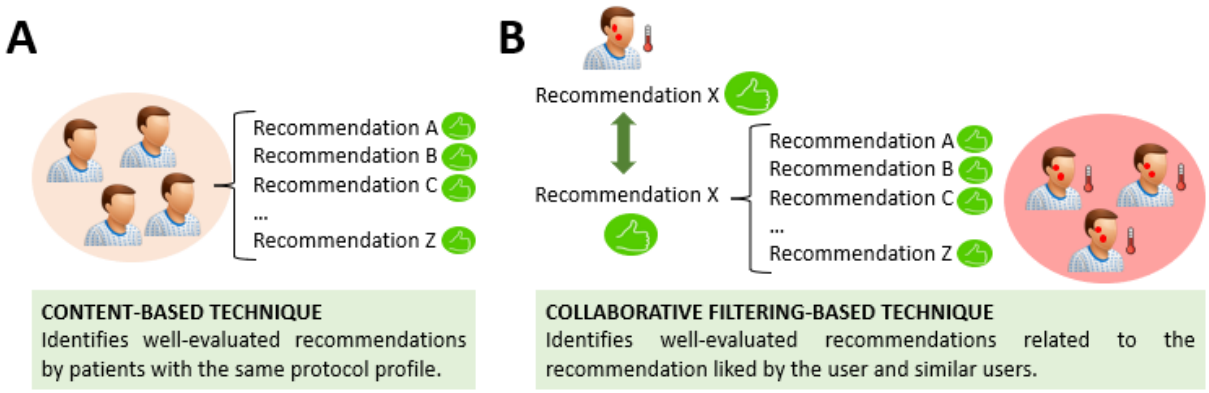
Table 37: Recommendations between the fourth and fifth chemotherapy sessions of the second case study.

Symptoms/Adverse Effects	Recommendations	Rating
Peripheral neuropathy	• To reduce tingling, the recommendation is to practice physical activity. Need to walk even with the tingling. It is necessary to walk to stimulate circulation for the adverse effect to improve. The suggestion is to walk around the court at home, indoors, or take a light walk around your home. It is important to stimulate your body's circulation.	5
	• Have a fabric glove in the kitchen (usually in the place where you have more contact with cold surfaces or objects), and avoid going barefoot (try to always wear tighter socks or shoes), especially when you feel more sensitive.	5
Hair loss	• It is recommended not to wash your hair every day. Avoid washing your hair too often. Avoid brushing your hair several times a day. Some attitudes will help ease the period of hair loss, but there is no way to prevent hair loss.	5
	• Cut your hair if you feel more comfortable when you notice hair loss.	5
Pain	• The recommendation is to continue taking the medications as recommended by the doctor (continue monitoring). If you are unable to take your pain medication, it is recommended that you contact your doctor as soon as possible.	3

6.3.1.3 Evaluation of the Recommendations

The content-based technique allowed for recommending guidelines well-evaluated by patients with the same protocol. The technique based on collaborative filtering made it possible to recommend guidelines that were well-evaluated by other similar patients. Thus, recommendations related to recommendations liked by the user and similar users have been prioritized and suggested to the target user. Therefore, in our examples, recommendations were given based on items well-rated by patients under the mFolfox6 protocol and/or items related to the item liked by the patient and similar patients, as seen in Figure 41.

Figure 41: Representation of the recommender system using the (A) content-based technique and (B) the collaborative filtering-based technique.



6.3.2 Discussion

This case study describes developing a recommender system integrated with the SMT model that provides tailored recommendations for colorectal cancer patients based on their reports and profile, and assessments performed by similar patients. This system uses machine learning in the design of the recommendation algorithm to provide tailored information, and it uses content-based and collaborative filtering techniques. In a preliminary case study, we assessed that the system can respond positively to user expectations. In the literature, we identified several studies in the context of applying a recommendation system in the oncology area (ORMEL et al., 2021; PARK et al., 2020; RANI; KAUR; KUMAR, 2022). However, to the best of our knowledge, this is the first study that addresses recommendations for symptoms and adverse effects perceived during active cancer treatment.

Ormel et al. (ORMEL et al., 2021) developed and evaluated an application that recommends videos with experiential information from women diagnosed with breast cancer to breast cancer patients undergoing surgery. It used content-based (suggesting videos of

speakers with similar characteristics to the user) and collaborative filtering (videos related to videos liked by the user and similar users) techniques. The pilot study results suggest a positive response in meeting patients' needs regarding the content and value of this type of tool (ORMEL et al., 2021).

Narducci et al. (NARDUCCI; LOPS; SEMERARO, 2017) designed a recommendation system that suggests doctors or hospitals that best relate to the health problem reported by the user. The system used NLP techniques to identify users' clinical status and symptoms in a natural language sentence. The system used a collaborative filtering technique, and the condition, symptoms, and treatment characteristics were the basis for calculating the similarity between patients (NARDUCCI; LOPS; SEMERARO, 2017).

Park et al. (PARK et al., 2020) developed a chemotherapy recommender model for patients with colorectal cancer after surgery. The system was based on deep learning techniques. The results were promising compared to machine learning techniques, protocols, and guidelines. They suggested an additional tool to be used to identify chemotherapy protocols for patients with colorectal cancer.

Rani et al., through an experimental study, proposed a recommender system to predict breast cancer diagnosis using a hybrid machine learning technique (RANI; KAUR; KUMAR, 2022). Ihnaini et al. designed a recommended system to predict multidisciplinary diabetes in patients using deep machine learning and data fusion techniques (IHNAINI et al., 2021).

In the present study, during the application of the SMT model, we observed the main symptoms and adverse effects reported by patients during CRC treatment. Thus, based on these data, we designed the recommender system coupled to the SMT model, where it was possible to generate several simulations of personalized recommendations for better patient guidance. Moreover, we can observe the relevance of the recommendation system in the health area and relevant preliminary results reported by recent studies. For future work, we suggest implementing and applying the recommendation system in patients in the active phase of treatment to assess its usability and address user expectations.

7 CONCLUSION

In the systematic review, it was observed that the main information monitored by the wearable devices were the calm state of the brain, heart rate and oxygen saturation levels, physical activity, energy expenditure and calories burned, sleep patterns, and circadian rest-activity rhythm. Furthermore, the use of wearable devices in cancer patients undergoing active treatment showed significant results, such as IoT combined with personalized interventions demonstrated to be an effective technique to improve the quality of life and self-management of adverse effects related to cancer treatment. This survey also identified some challenges that need to be addressed, such as patient engagement, technology skills, and constant or periodic feedback. Finally, it was identified that most of the studies were pilots, and, in general, the applied tools were being evaluated for the first time, which indicated to be a recent issue.

Thus, we propose a new computational model for monitoring cancer patients undergoing active treatment using IoT and artificial intelligence. In the first evaluation stage, through a pilot study, we evaluated the use of the chatbot. It was observed that the chatbot provided a good experience and usability to users. Chatbot was highly rated in both the UEQ and SUS questionnaires. All the participants' scores on the UEQ scales were rated as good or excellent, suggesting that they were satisfied with their chatbot experience. The mean SUS score was 75, and the median was 72.5, indicating that the system has acceptable usability.

Our results demonstrated that the chatbot effectively addressed usability and user experience. This is an important finding because this new model can contribute to the patients' quality of life and bring them closer to the multidisciplinary team that accompanies them during the treatment. We updated the model based on the evaluations and feedback from the pilot study and then applied the proposed computational model to CRC patients.

In the second evaluation stage, through a prospective non-randomized clinical study, we observed that the model contributed to more accurate self-reporting of symptoms and adverse effects during the active treatment phase, which allowed for a closer relationship between the clinic's multidisciplinary team and patients. The results suggest that the model contributed to the performance of the physical activity, greater patient engagement with their treatment, addressed patient expectations, and was considered acceptable usability.

We observed that self-report symptoms, such as fatigue and lack of appetite, and adverse effects, such as hair loss, nausea/vomiting, insomnia, constipation, and peripheral neuropathy, were significantly higher in the intervention group when compared to the control group. Furthermore, we observed that the model contributed to an increase in the practice of physical

activities. Thus, the results indicate that our model addressed the research question proposed for this thesis since the findings suggest that our model contributed to increasing patient engagement, providing better monitoring of their clinical condition.

Moreover, the model may have contributed to a change in the patient's behavior. Most patients consumed carbohydrates, fast food, red meat, and alcohol, and few practiced physical activities. The results suggest that the intervention through the application of the model contributed to an increase in the consumption of fruits and the practice of physical activity, in addition to helping to reduce the intake of alcoholic beverages and the consumption of fast food.

Finally, we conclude that the main contributions of this work are the development and application of a novel model for monitoring CRC patients during the active treatment phase; greater cancer patient engagement; closer support from the medical team to the patient providing a better quality of life; and automated and individualized feedback between patient and multidisciplinary team according to the interaction performed.

For future work, we suggest applying this model to patients with other types of cancer to assess and extend the benefits of the model in different contexts of oncological treatment and extend the period of model application during all chemotherapy sessions. We also suggest applying the SMT model integrated into the recommender system to evaluate the benefits, usability, and user experience.

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APPENDIX 1 - DEMOGRAPHIC AND CLINICAL DATA

The following demographics data are expected to be collected on the day of the patient's diagnostic appointment and/or 1st chemotherapy session:

- age (date of birth);
- sex (male or female);
- year of cancer diagnosis (date);
- participant's occupation (examples: student, worker and retiree) and time of dedication (full-time, part-time, none);
- ethnicity or race;
- highest level of education;
- current city of residence.

It is planned to collect the following clinical data in each chemotherapy session:

- weight and height;
- blood pressure;
- oximetry;
- temperature.

APPENDIX 2 - INFORMED CONSENT FORM

Projeto: *Smart Monitoring Tool*: Modelo Inteligente para o Monitoramento de Pacientes com Câncer Colorretal na Fase Ativa do Tratamento

Você está sendo convidado(a) a participar de uma pesquisa cujo objetivo é propor um novo modelo inteligente de acompanhamento de pacientes com câncer colorretal em fase de tratamento ativo por meio do uso de inteligência artificial e internet das coisas. Esta pesquisa está sendo realizada pela Universidade do Vale do Rio dos Sinos (UNISINOS) em parceria com o Centro do Câncer de Sinop (Cecans). Se você aceitar o convite, sua participação na pesquisa envolverá o uso de aplicativo de celular e *wearable device* (ferramenta para coleta de dados, como, por exemplo, uma pulseira inteligente). Além da equipe do Cecans, a pesquisa será acompanhada pelos pesquisadores responsáveis pelo projeto Cristiano André da Costa e Diogo Albino de Queiroz que possuem formação na área de Computação.

O aplicativo tem como objetivo interagir com você sobre os sinais/sintomas relacionados ao câncer e efeitos adversos relacionados ao tratamento. De acordo com os dados informados, você receberá feedbacks da ação a ser tomada e a equipe multidisciplinar poderá receber uma notificação em tempo real da sua condição clínica. Não iremos realizar diagnósticos, iremos somente reforçar as orientações que foram dadas pelo médico. O aplicativo poderá interagir com você por meio de troca de mensagens a partir do seu relato e poderá te estimular a interagir com ele a partir de questões as quais você estará submetido durante o seu uso. O *wearable device* tem como objetivo coletar dados sobre quantidade de passos e distância percorrida por você durante a realização das atividades físicas propostas pelo médico.

O uso do aplicativo e do *wearable device* podem gerar desconfortos e dificuldades no uso devido à falta de conhecimentos tecnológicos ou pelo fato de você não entender as perguntas/atividades propostas, entretanto, o pesquisador sempre estará à disposição para esclarecer as suas dúvidas e apoiar no seu uso. Ainda, podem ser gerados desconfortos emocionais durante o uso de tais ferramentas devido ao estado clínico que você se encontra, entretanto, o pesquisador estará à disposição para te auxiliar e acionar a equipe multidisciplinar caso necessário. Além disso, caso você não se sinta confortável em continuar com o uso, poderá interromper de forma momentânea ou definitiva o uso.

Como benefício você contribuirá, de forma indireta, para o levantamento de dados que auxiliarão na melhor compreensão sobre os efeitos do câncer e do seu tratamento. Ainda, você contribuirá para o desenvolvimento e validação de um novo modelo de monitoramento de pacientes com câncer colorretal em fase de tratamento ativo que tem o intuito de melhorar o engajamento do paciente ao tratamento. De forma direta você receberá orientações sobre sinais e sintomas decorrentes da doença e os efeitos adversos decorrentes do tratamento, além de orientações sobre a prática de atividades físicas.

Sua participação na pesquisa é totalmente voluntária, ou seja, não é obrigatória. Caso você decida não participar, ou ainda, desistir de participar e retirar seu consentimento, não haverá nenhum prejuízo ao vínculo institucional. Não está previsto nenhum tipo de pagamento pela sua participação na pesquisa e você não terá nenhum custo com respeito aos procedimentos envolvidos. Caso ocorra alguma intercorrência ou dano, resultante de sua participação na pesquisa, você receberá todo o atendimento necessário, sem nenhum custo pessoal.

Os dados coletados durante a pesquisa serão sempre tratados confidencialmente e todos os pesquisadores envolvidos se comprometem com o sigilo das informações. Os resultados serão

apresentados de forma conjunta, sem a identificação dos participantes, ou seja, o seu nome não aparecerá na publicação dos resultados.

Caso você tenha dúvidas, poderá entrar em contato com os pesquisadores responsáveis Cristiano André da Costa, pelo telefone (51) 3590-8161 ou (51) 99994-4000, ou Diogo Albino de Queiroz, pelo telefone (66) 99962-5677.

Também, se houver dúvidas quanto aos aspectos éticos da pesquisa, você poderá entrar em contato com o Comitê de Ética em Pesquisa (CEP) da Universidade do Vale do Rio dos Sinos (Unisinos), localizado na sala A01 - Centro Comunitário - Unidade de Pesquisa e Pós-Graduação (UAPPG), Av. Unisinos, 950, CEP 93022-000 – São Leopoldo/RS, telefone: (51) 3591 1122 Ramal 3219, e-mail: cep@unisinos.br .

Após a leitura completa deste termo eu, _____, declaro que compreendi os objetivos do estudo "*Smart Monitoring Tool*: Modelo Inteligente para o Monitoramento de Pacientes com Câncer Colorretal na Fase Ativa do Tratamento" que será conduzido pelos pesquisadores Cristiano André da Costa e Diogo Albino de Queiroz. Também declaro que recebi uma via deste Termo de Consentimento Livre e Esclarecido, ficando outra via com o pesquisador, e que estou de acordo com a participação voluntária nesta pesquisa.

Esse Termo é assinado em duas vias, sendo uma para o participante e outra para os pesquisadores.

_____

Nome do participante da pesquisa

_____

Assinatura

_____

Nome do pesquisador que aplicou o Termo

_____

Assinatura

Local e Data: _____